
Geospatial Visual Analytics:

Visual analysis of spatio-temporal data

Part 3: behaviours of moving objects



Fraunhofer Institut
Intelligente Analyse- und
Informationssysteme

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<http://geoanalytics.net>

Types of Temporal Variance

- Changes of thematic properties (values of attributes) associated with places
 - e.g. district population, data from stationary sensors
- Existential changes (appearance and disappearance)
 - Events: objects with limited life time
 - e.g. earthquakes, traffic incidents, observations of rare plants or animals
- Changes of spatial properties: location, size, shape, orientation, altitude, etc.
 - e.g. movement of vehicles, growth of cities

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Analysis of movements of an individual (*person, animal, etc.*): major tasks and typical problems

- Investigate the movement behaviour of the object:
 - Detect and interpret typical trips: sources, destinations, routes, intermediate stops, purposes, ...
 - Find out the typical times of the trips
 - If possible, interpret also atypical trips (e.g. unusual route, timing, duration, ...)
 - Problems:
 - no explicit trips in the data but just positions
 - no meaningful places but coordinates
- ⇒ Places and trips have to be defined through data analysis!
- ✓ *In our example, we know that the positions were recorded only while the car moved. Otherwise, the data could be filtered to remove sequences of records made in the same place (using an appropriate distance threshold).*
- Problem: the position records are too numerous to be examined by a human analyst
- ⇒ The use of database processing and computational techniques is strictly necessary!

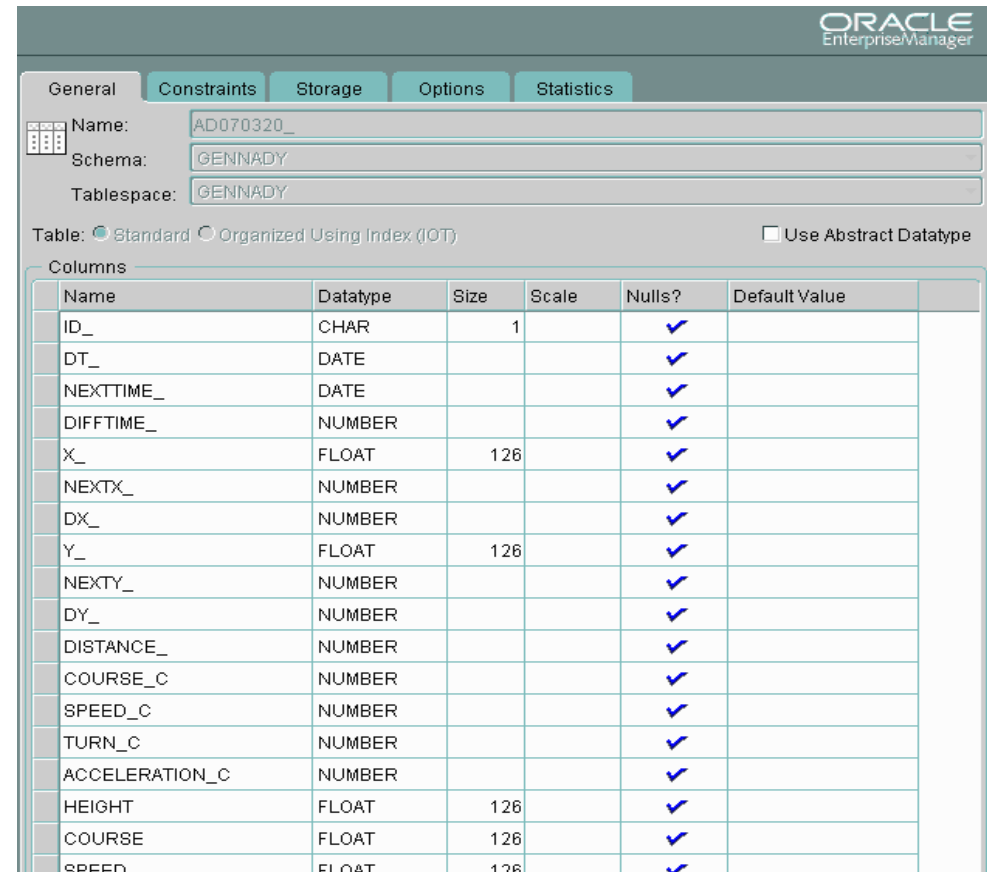
Data preprocessing (one-time operation in DB)

Original data:

- $\langle t, x, y \rangle$

Results of preprocessing:

- Points are arranged into temporally ordered sequences (NEXTTIME field)
- Computed distances in space and time to the next position (DIFFTIME and DISTANCE)
- Derived speed, course, acceleration and turn in each point
- Temporal components are easy to extract: day of week, day of year, decade of month...



Oracle Enterprise Manager interface showing the table definition for AD070320_ in the GENNADY schema. The table is a Standard table. The columns are:

| Name | Datatype | Size | Scale | Nulls? | Default Value |
|----------------|----------|------|-------|--------|---------------|
| ID_ | CHAR | 1 | | ✓ | |
| DT_ | DATE | | | ✓ | |
| NEXTTIME_ | DATE | | | ✓ | |
| DIFFTIME_ | NUMBER | | | ✓ | |
| X_ | FLOAT | 126 | | ✓ | |
| NEXTX_ | NUMBER | | | ✓ | |
| DX_ | NUMBER | | | ✓ | |
| Y_ | FLOAT | 126 | | ✓ | |
| NEXTY_ | NUMBER | | | ✓ | |
| DY_ | NUMBER | | | ✓ | |
| DISTANCE_ | NUMBER | | | ✓ | |
| COURSE_C | NUMBER | | | ✓ | |
| SPEED_C | NUMBER | | | ✓ | |
| TURN_C | NUMBER | | | ✓ | |
| ACCELERATION_C | NUMBER | | | ✓ | |
| HEIGHT | FLOAT | 126 | | ✓ | |
| COURSE | FLOAT | 126 | | ✓ | |
| SPEED | FLOAT | 126 | | ✓ | |

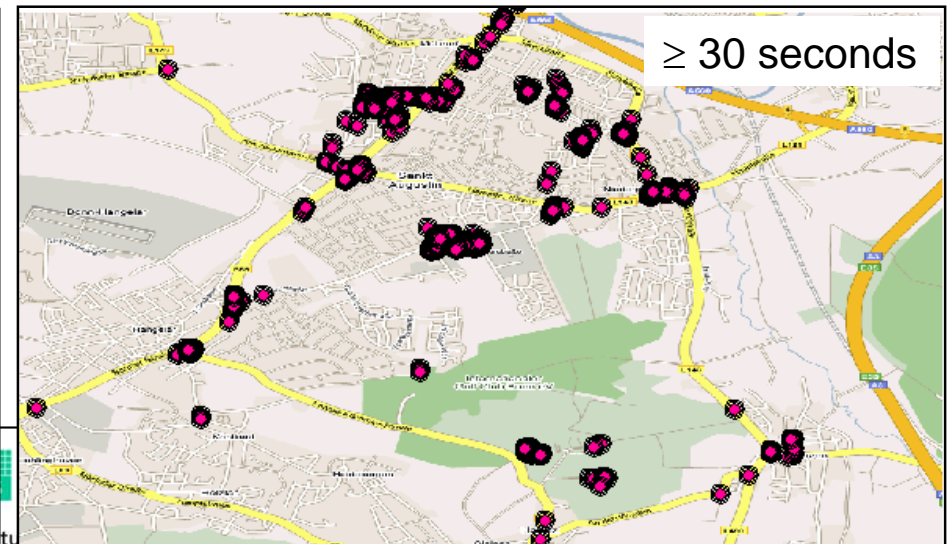
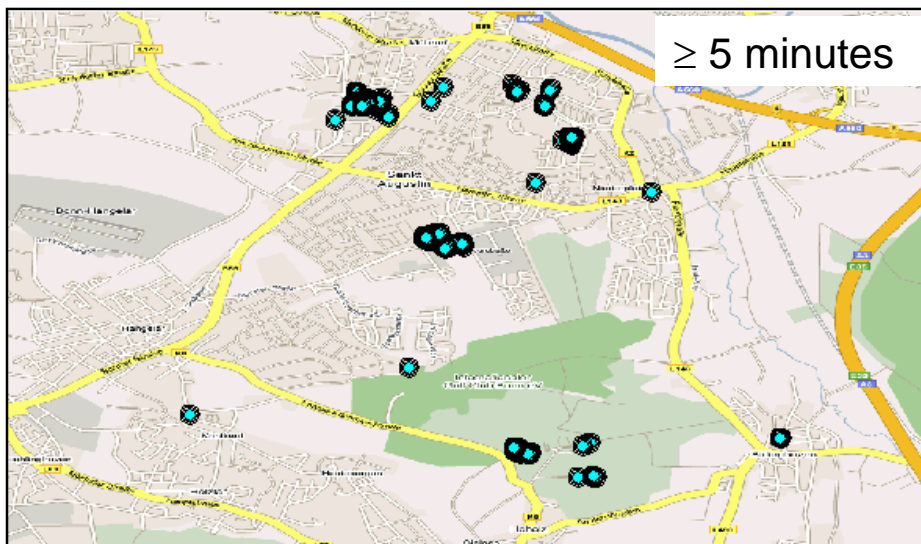
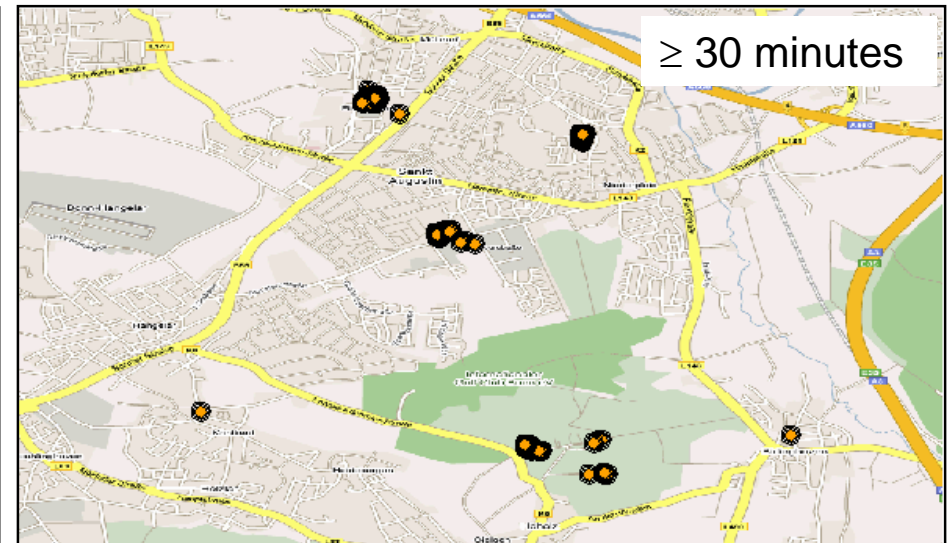
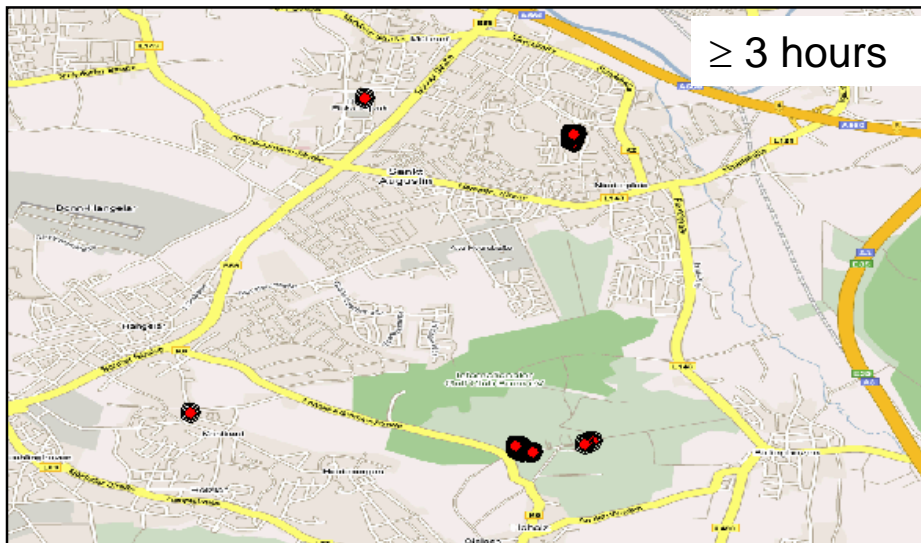
This time-consuming data pre-processing needs to be performed only once. It is therefore separated from further analysis and aggregation procedures.

Subtask 1: define significant places

- We know that the DB contains position records only for the times when the car moved.
 - ⇒ Large time gaps between successive positions indicate stops.
 - ⇒ We can query the database for the positions where DIFFTIME (distance in time to the next position) exceeds a specified threshold
- The possible meanings of the extracted places will differ depending on the threshold
 - Large gaps: places where the person spends much time (home, work)
 - Medium gaps: shops, doctors, sport facilities, ...
 - Small gaps: traffic lights, street crossings, ...
- Places separated by medium to large gaps may be destinations and sources of trips
 - ⇒ Sequences of positions between the gaps represent the trips

Extraction of the places of stops

DB query: select points where DIFTIME \geq chosen temporal threshold

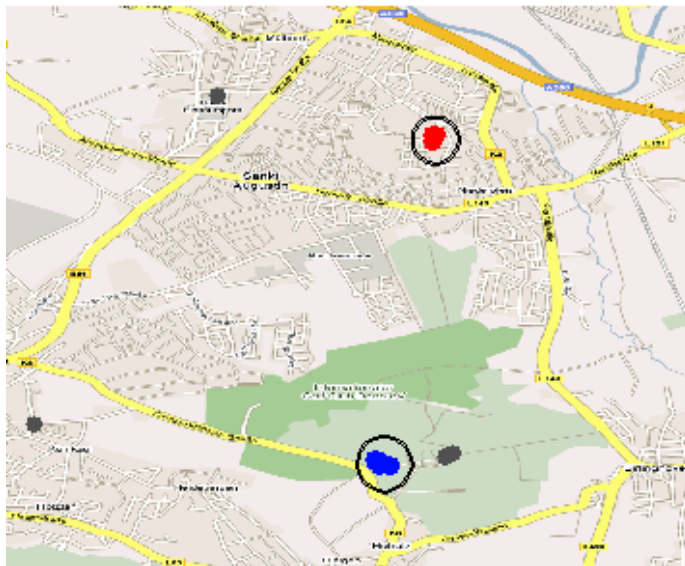


Interpretation of the places of stops

A) Long stops (≥ 3 hours)

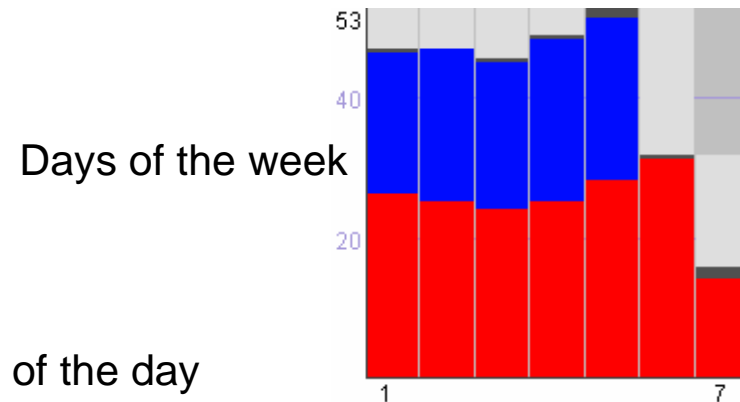
1) Spatial clustering: find places of repeated stops

(more significant than occasional stops)

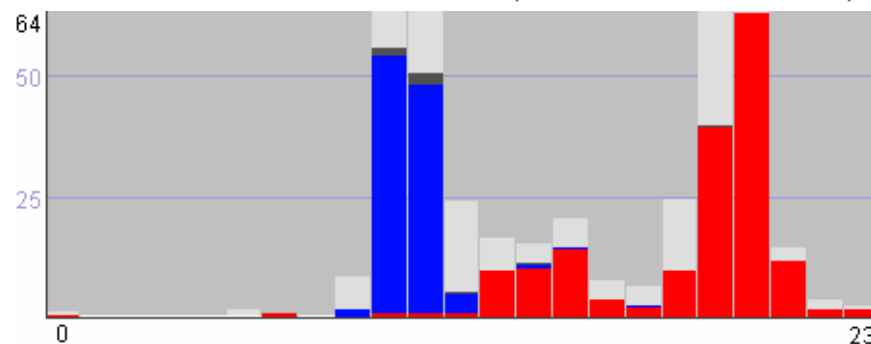


■ cluster 1: 173 objects (29.8%)
■ cluster 2: 109 objects (18.8%)
■ noise: 8 objects (1.4%)

2) Look at the days and times of the occurrence



Hours of the day

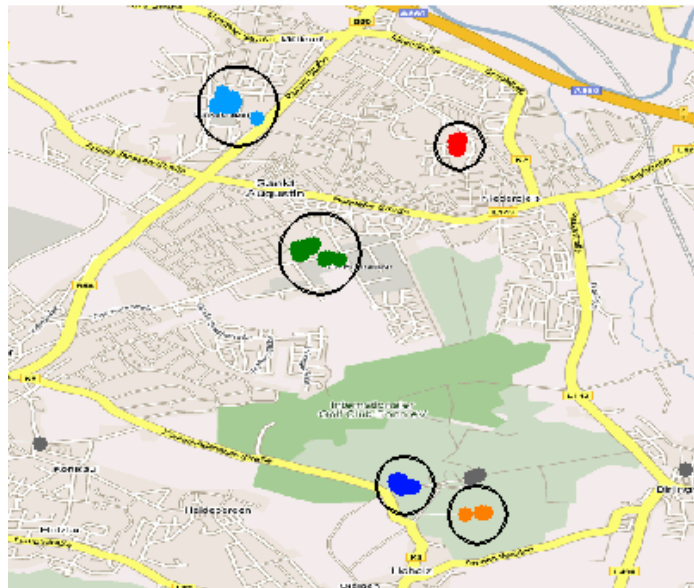


⇒ Red: home, blue: work

Interpretation of the places of stops

B) Medium stops (≥ 30 minutes)

1) Spatial clustering: find places of repeated stops

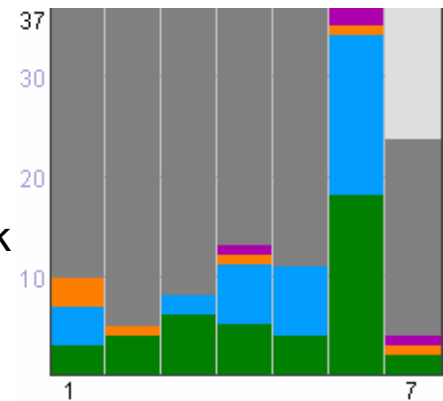


- cluster 1: 184 objects (22.7%)
- cluster 2: 117 objects (14.4%)
- cluster 3: 42 objects (5.2%)
- cluster 4: 35 objects (4.3%)
- cluster 5: 7 objects (0.9%)
- cluster 6: 4 objects (0.5%)
- noise: 17 objects (2.1%)

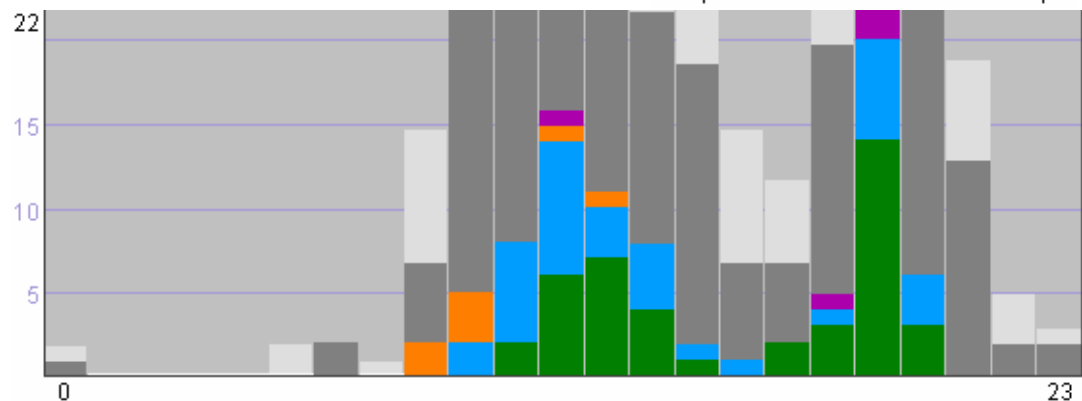
2) Look at the days and times of the occurrence

(clusters 1&2 excluded)

Days of the week



Hours of the day



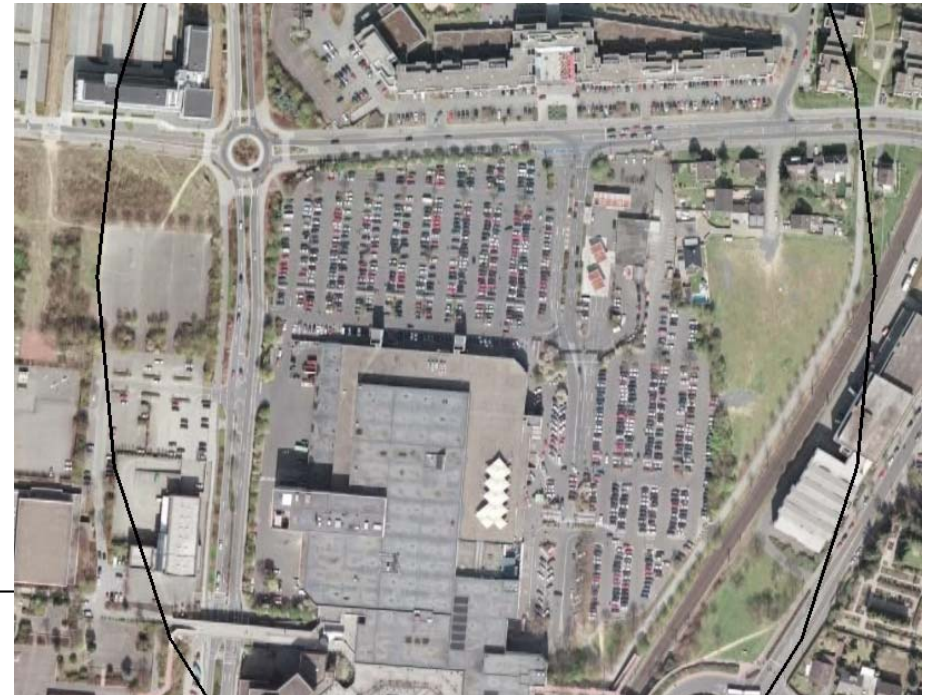
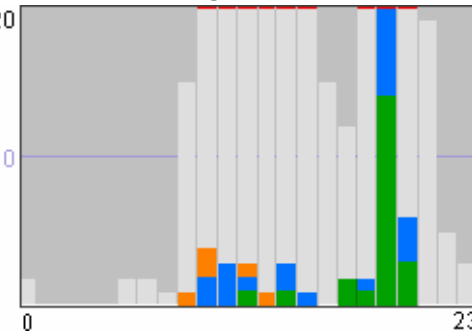
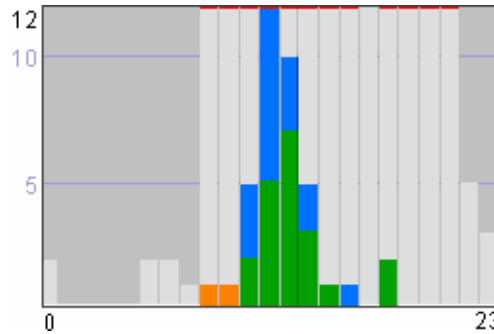
⇒ **Green & light blue: probably shopping**



Interpretation of the clusters 3 and 4 (continued)

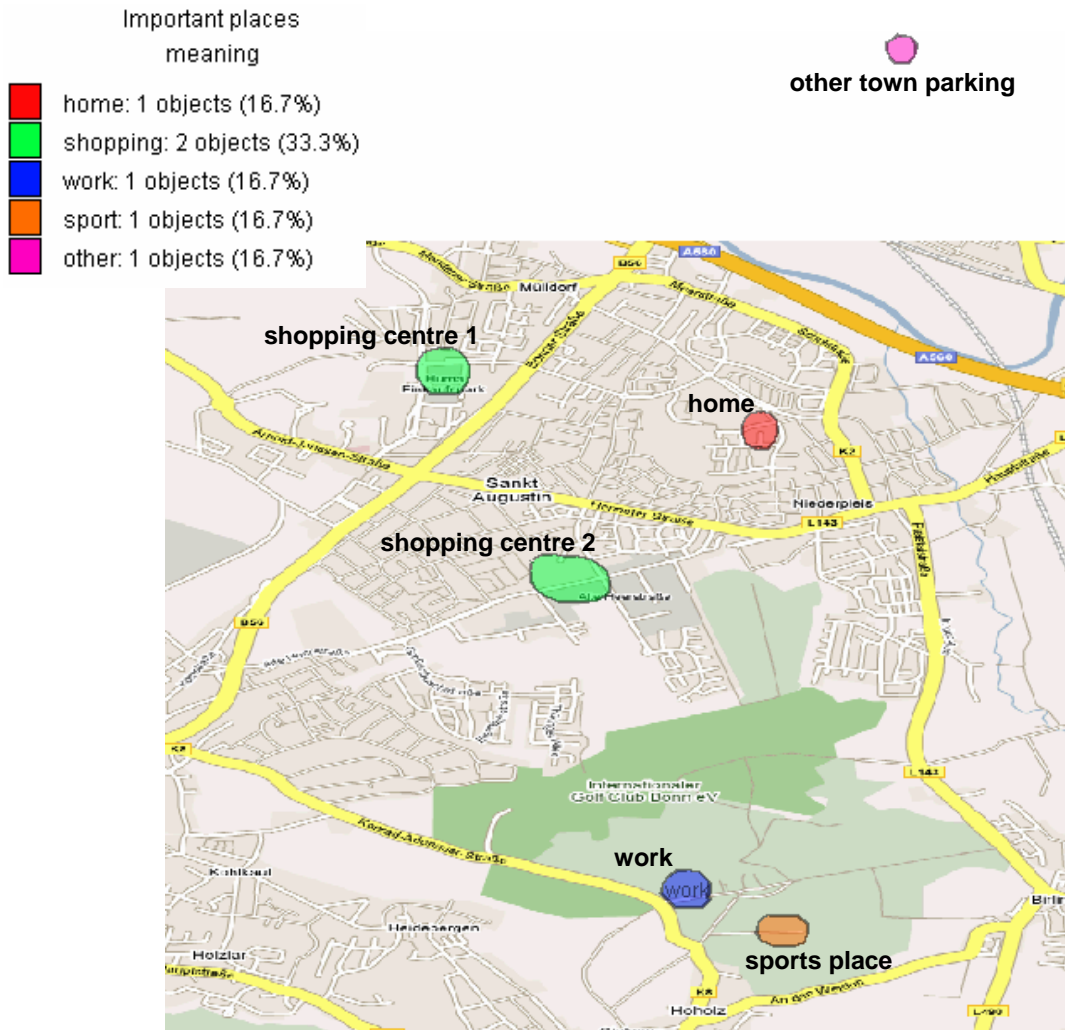
Saturday and Sunday: the stops mostly occur between 10 and 14

Monday to Friday: the stops mostly occur in the evening hours (max between 18 and 19)



Natalia & Gennady Andrienko

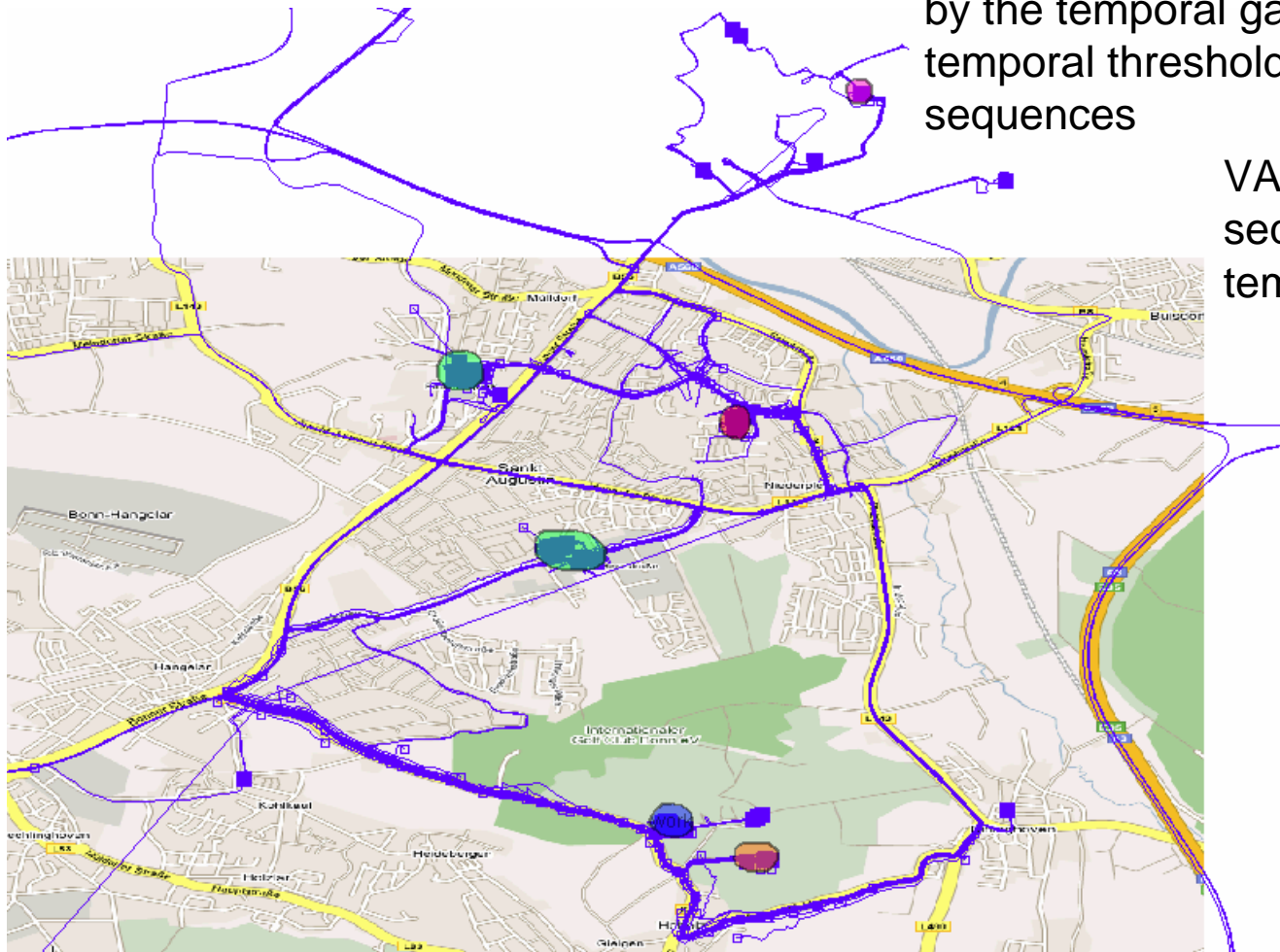
The interpreted places



Extraction of trips (trajectories)

DB query: divide the points into sequences by the temporal gaps ($\text{DIFTIME} \geq \text{chosen temporal threshold}$) and extract the sequences

VA toolkit: represent the sequences as spatio-temporal lines (trajectories)

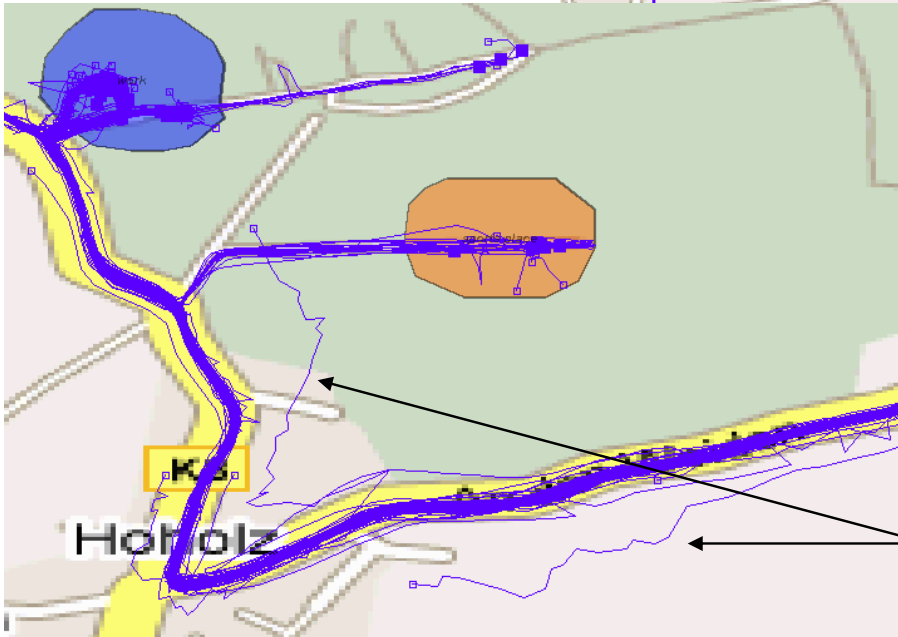
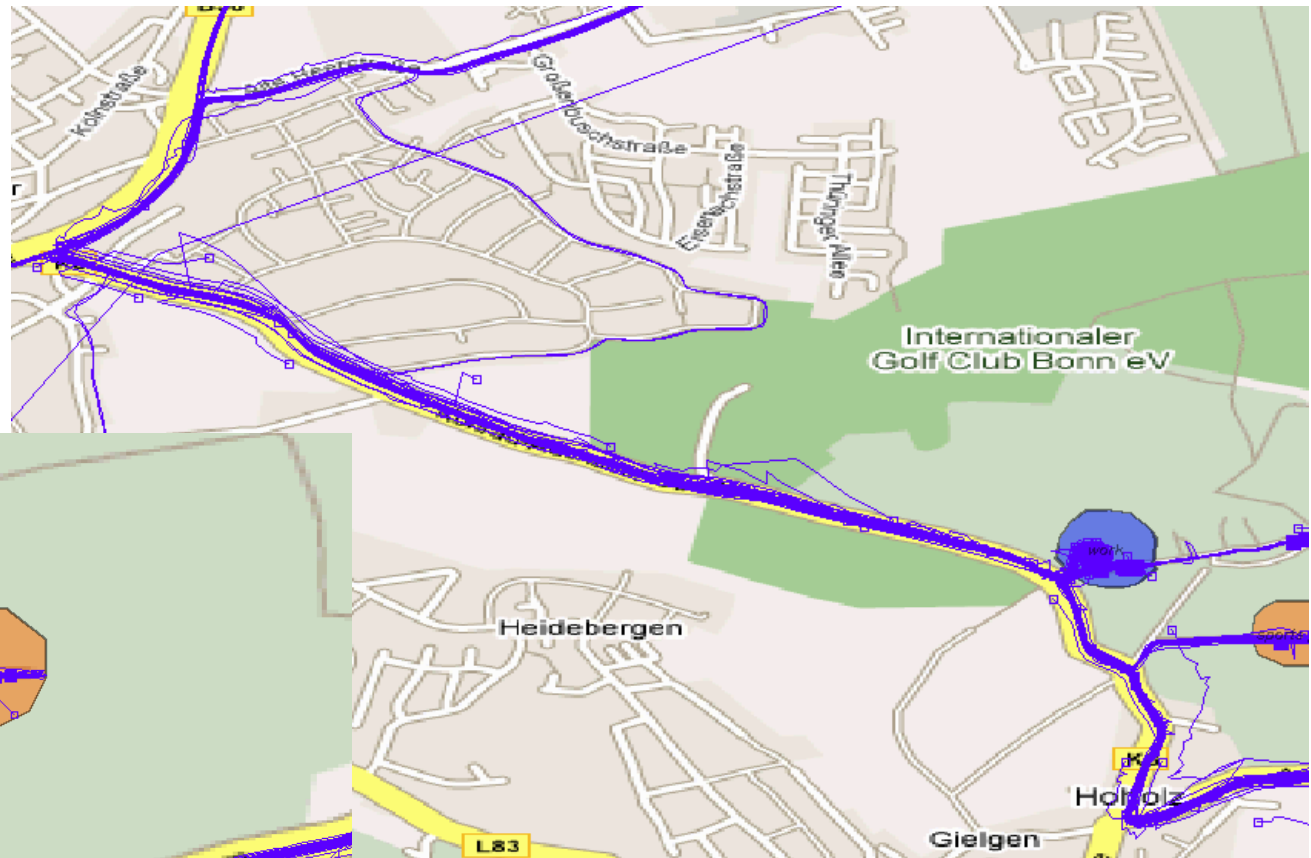


A trajectory in more detail



Problems with data quality...

Many false starts;
the real starts are missing



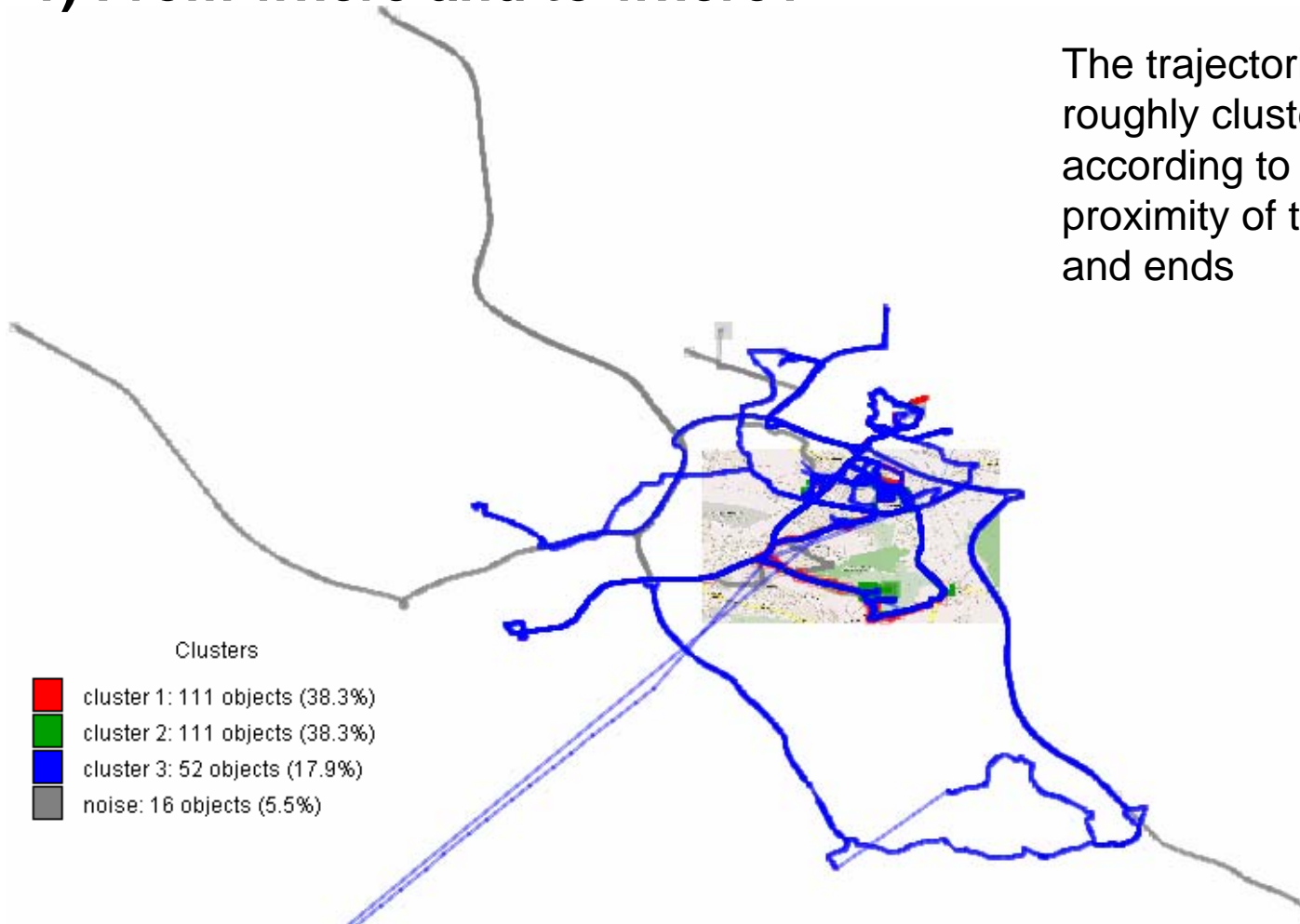
Positioning errors



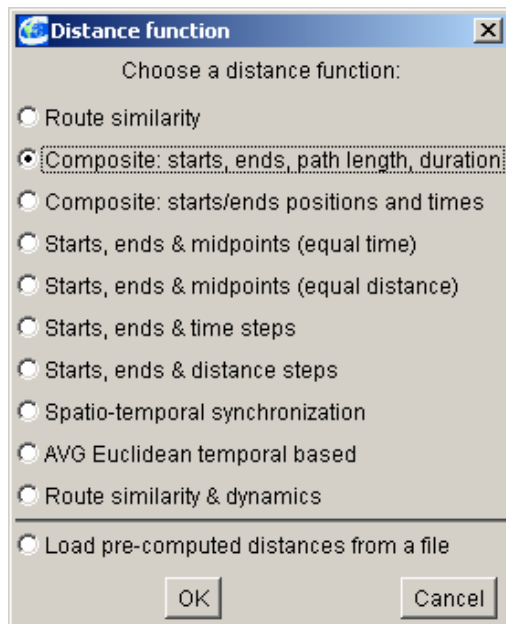
Looking for typical trips

1) From where and to where?

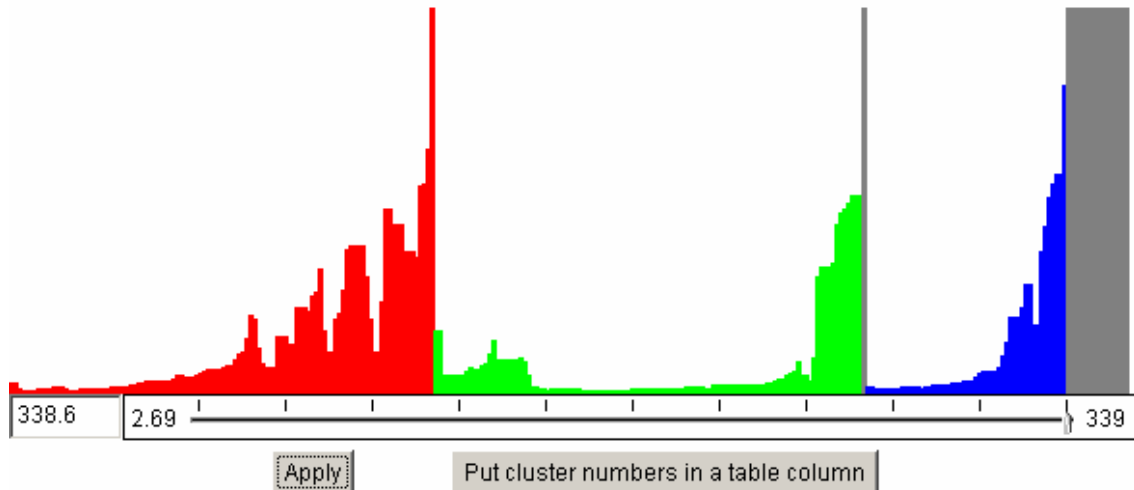
The trajectories are very roughly clustered according to the spatial proximity of their starts and ends



Interactive tool for spatial clustering

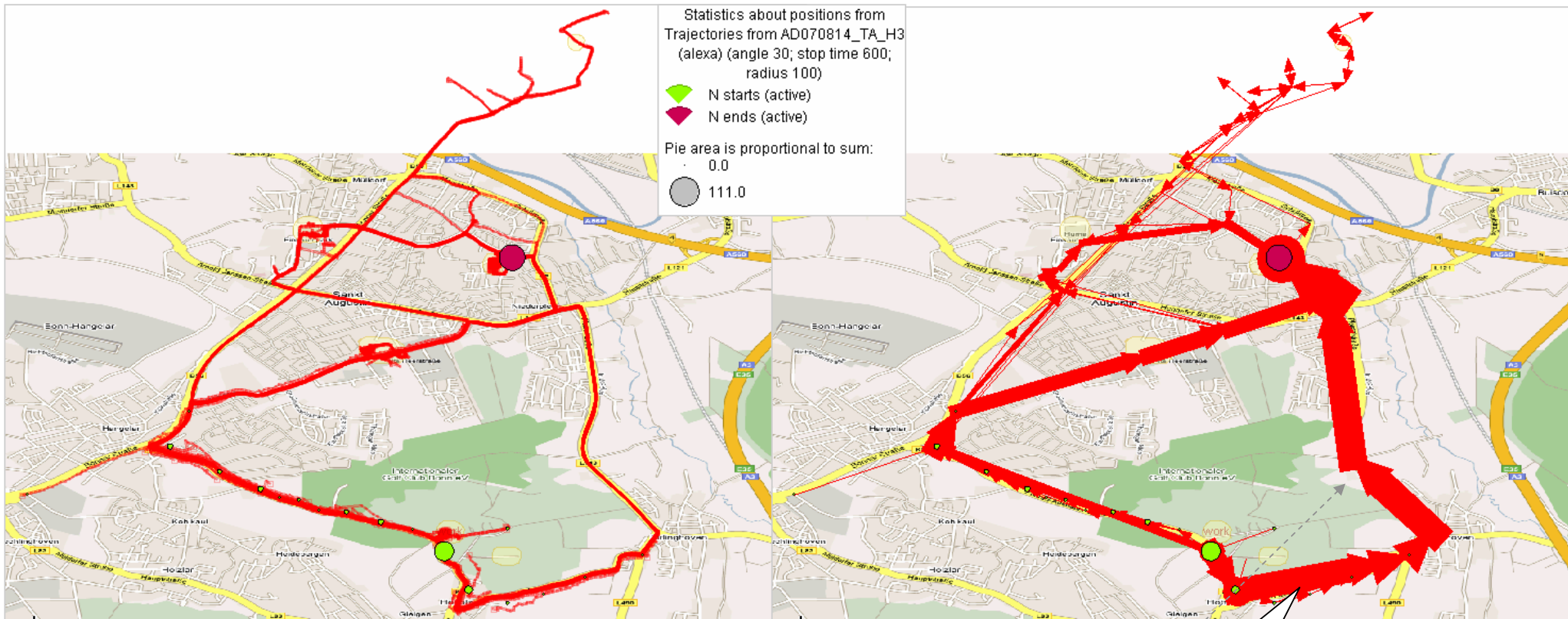


Clustered by OPTICS with distance threshold = 1200.0 and minimum number of objects = 3. Distance function: Starts & end



- spatial clustering algorithm OPTICS (*Ankerst, Breunig, Kriegel, and Sander 1999*)
- our implementation: cluster building is separated from distance and neighbourhood computation
- benefit: an analyst may try different distance measures
- there are several variants of distance measures designed specially for trajectories
- most of the measures can tolerate the specific errors in GPS-collected data

Cluster 1: from around the work to home (111 trips)



Summarised representation of multiple movements

Summarisation of trajectories: how it is done (1)

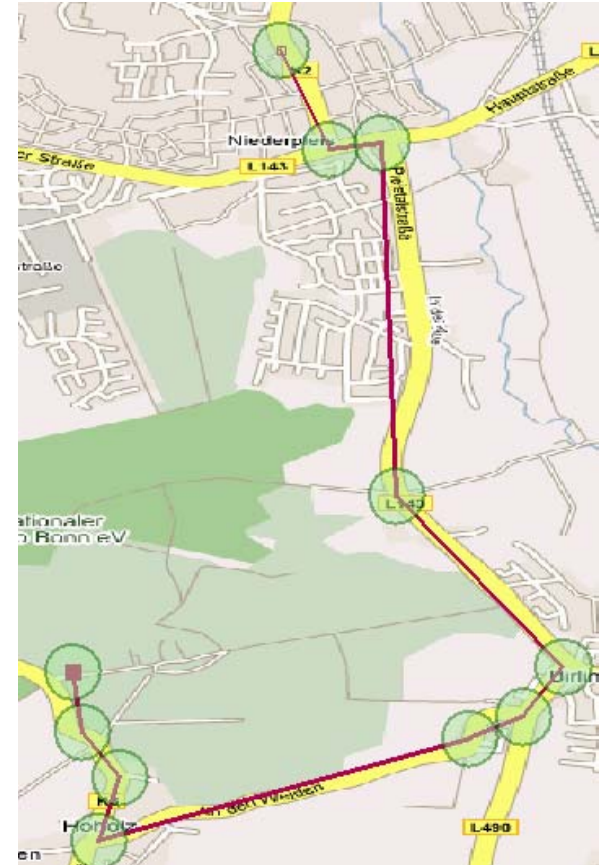
Original trajectory



Simplified trajectory



Generalised positions

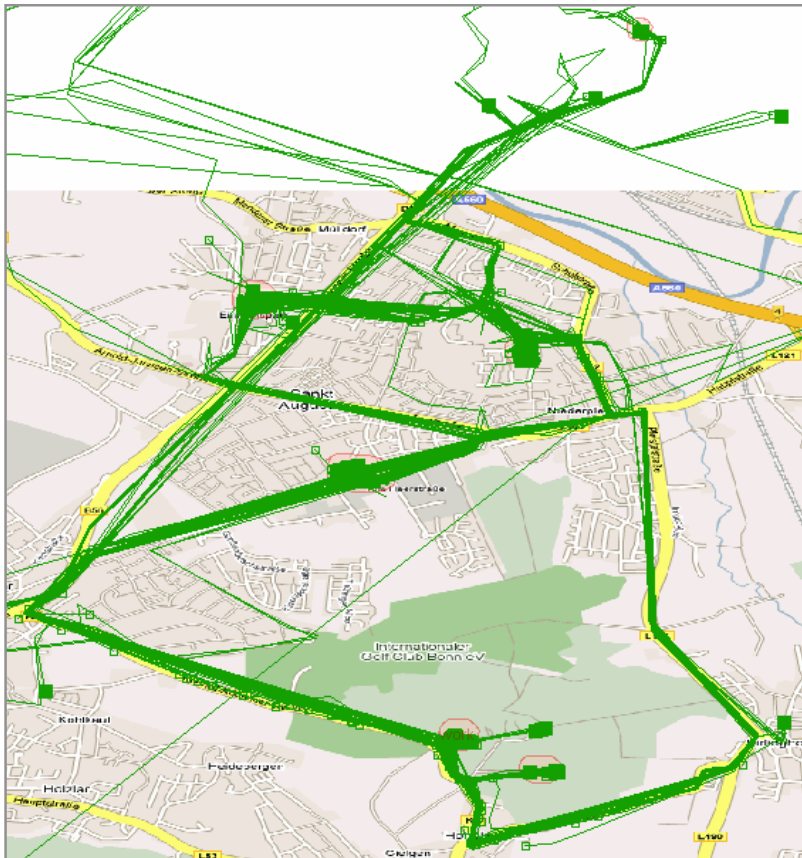


| | |
|--|-------|
| Minimum angle of direction change (degrees): | 30 |
| Minimum duration of a stop: | 60 |
| Minimum radius around a position: | 100.0 |

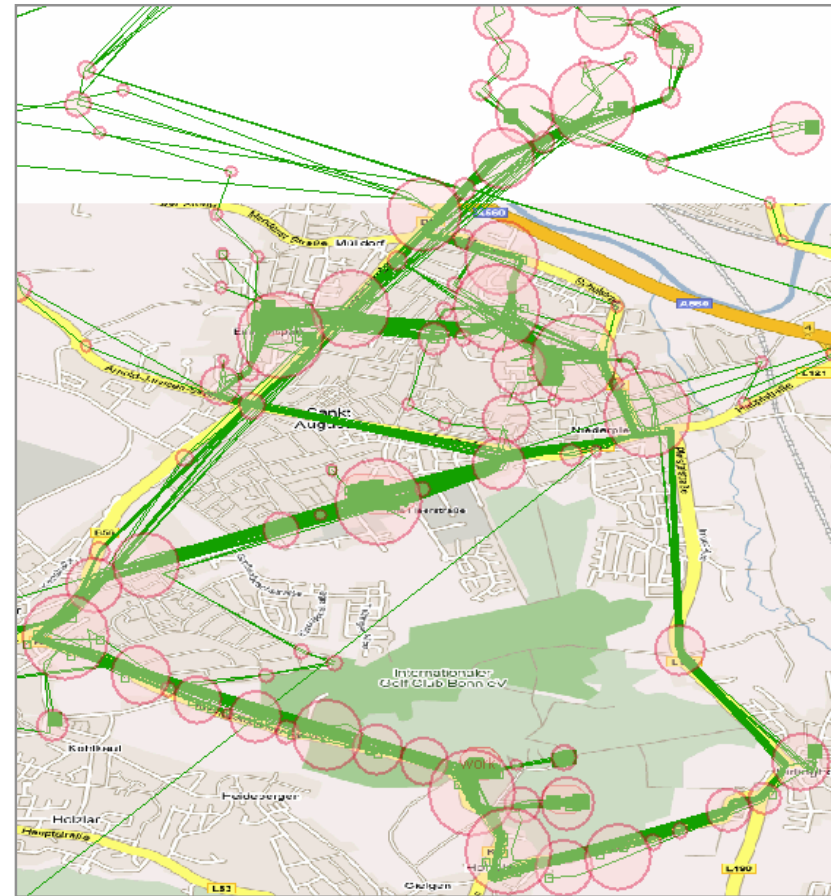
← Specifies which positions to keep



Summarisation: how it is done (2)

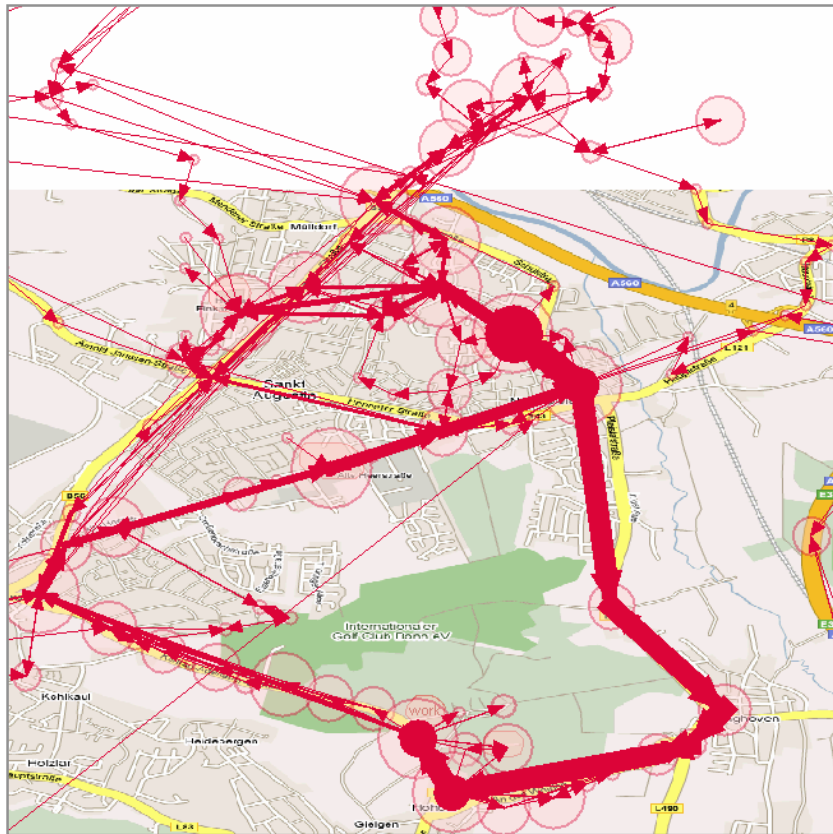


All trajectories simplified

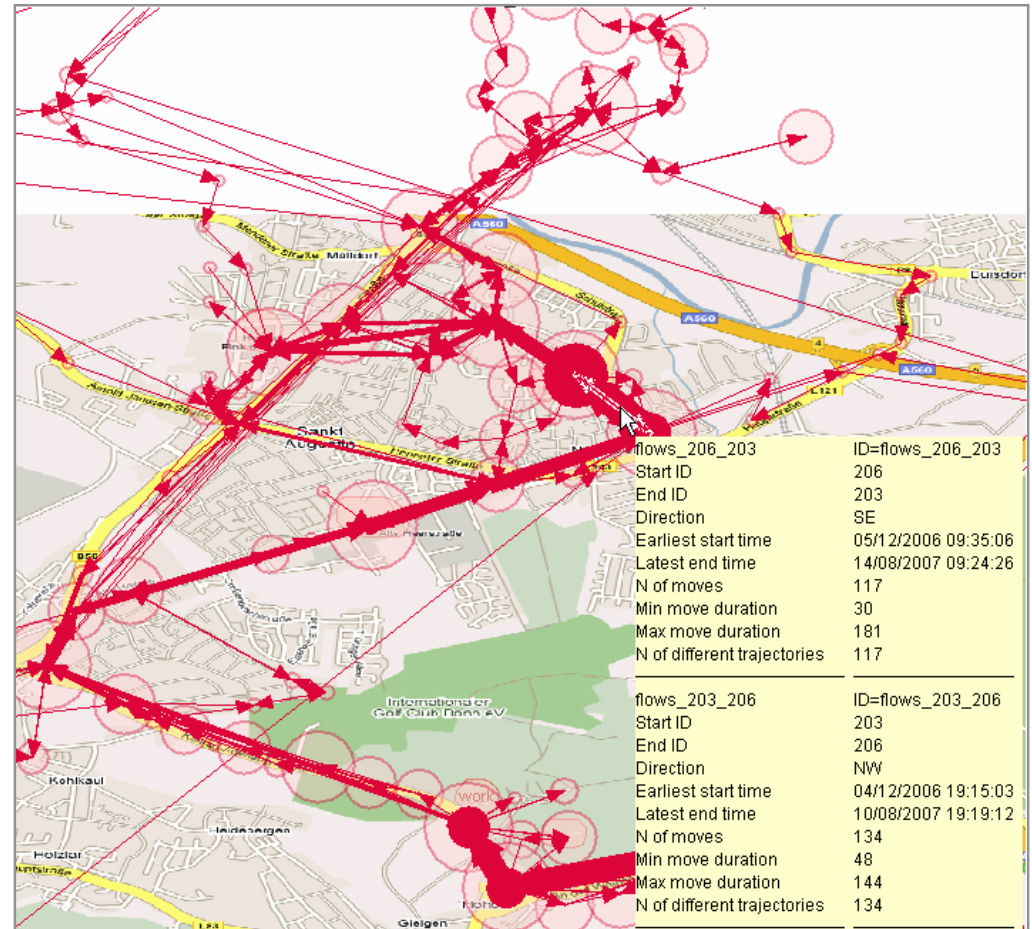


Generalised positions (circles, for simplicity) are built around spatially close positions of all trajectories

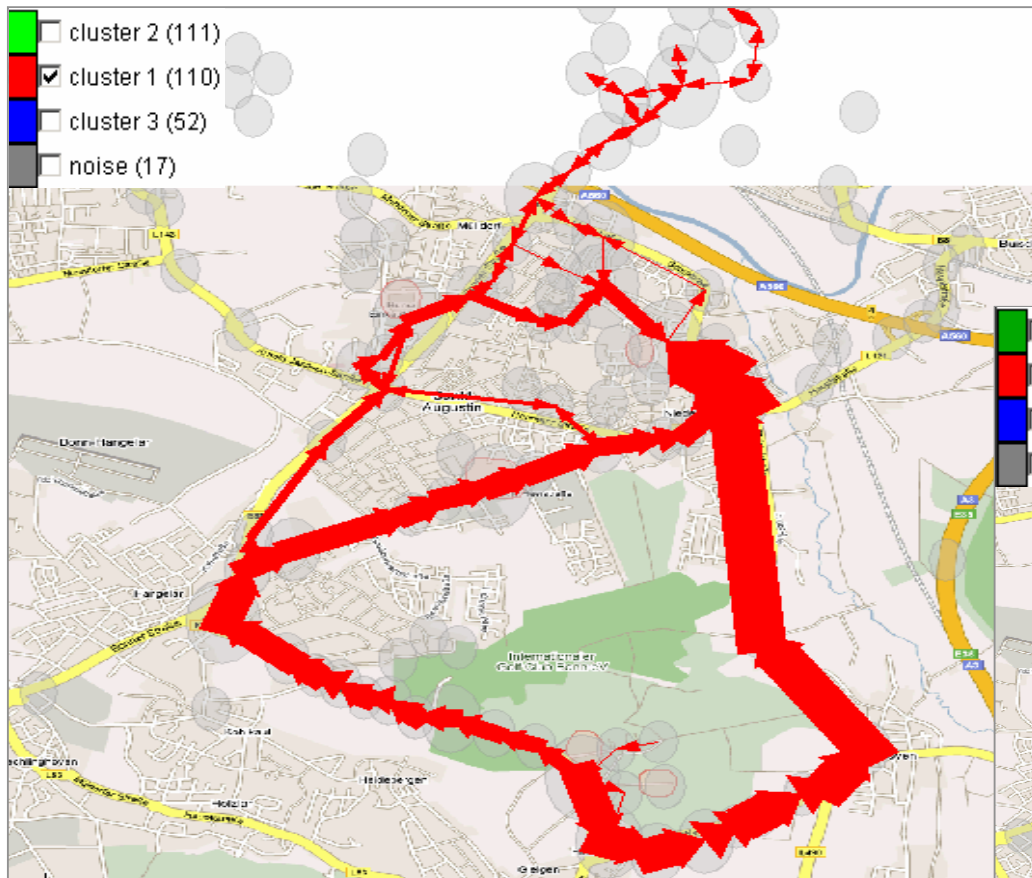
Summarisation: how it is done (3)



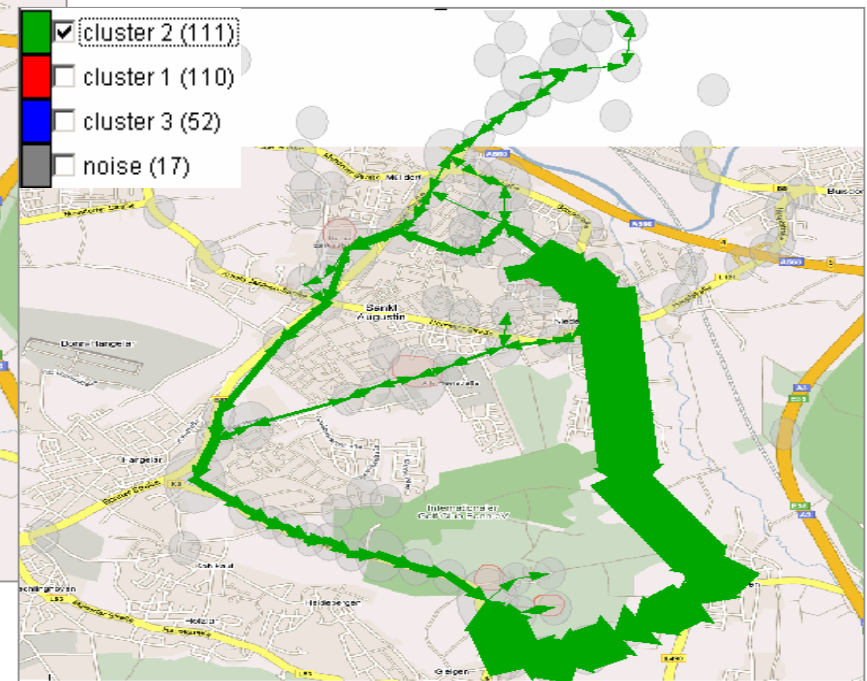
Numbers of moves between the circles are counted and represented by arrows of varying width



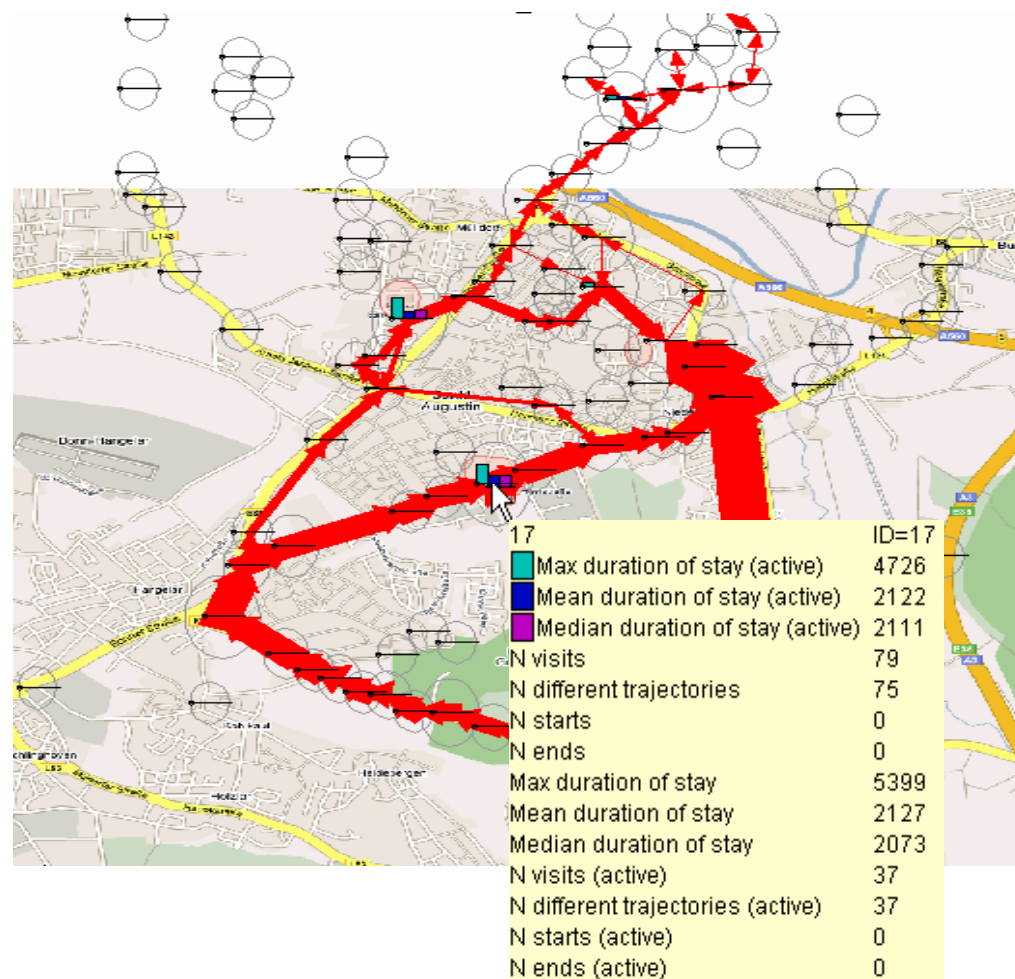
Summarisation: how it is done (4)



When a single cluster is selected (or any other filter is applied to trajectories), the aggregate moves represent only those trajectories that are currently active



Summarisation: how it is done (5)



Generalised positions from Trajectories (3 hours gap) (angle 30; stop time 60; radius 100-200)

Representation method: Parallel bars

Statistics about positions from Trajectories (3 hours gap) (angle 30; stop time 60; radius 100-200)

- Max duration of stay (active)
- Mean duration of stay (active)
- Median duration of stay (active)

→ 10793

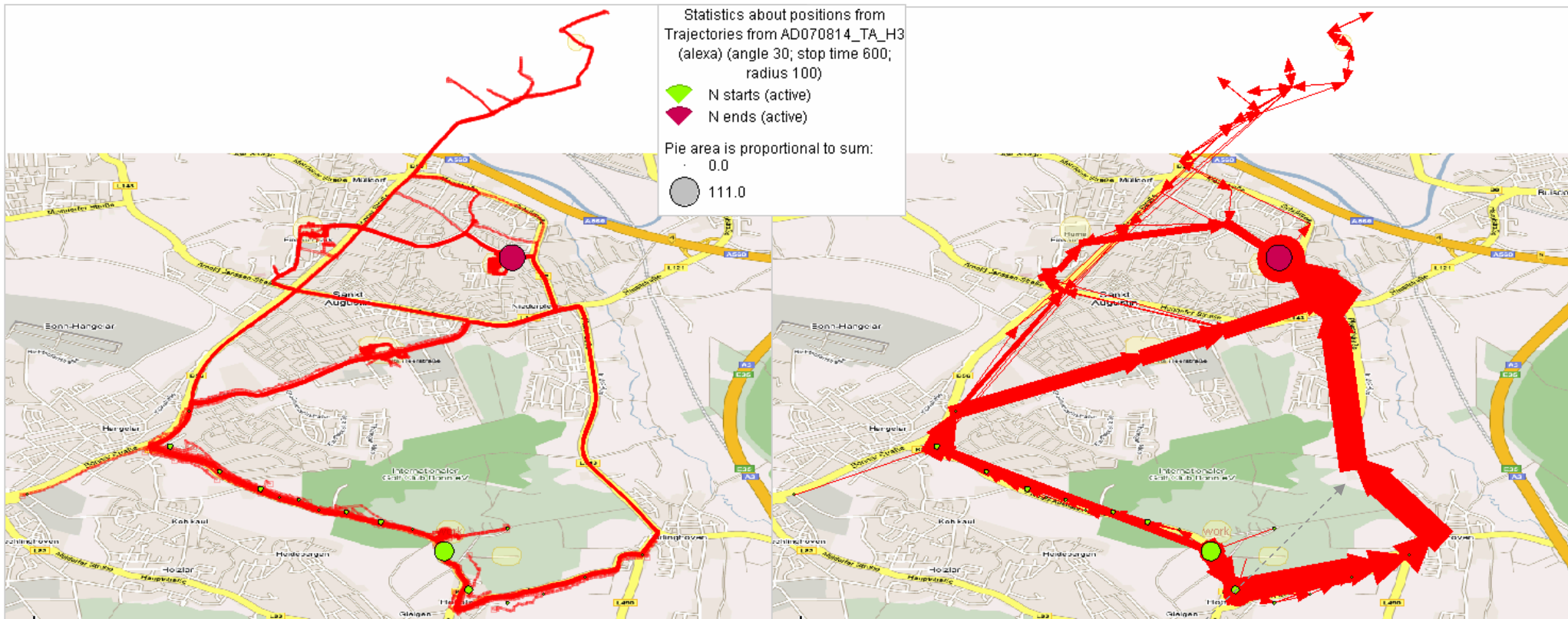
→ 0

Total: 212 objects

The movement data are also summarised by the generalised positions (circles). When the selected subset of active trajectories changes, the corresponding attributes of the circles are re-computed (these are thus *dynamic attributes*).

Various visualisation techniques can be applied to both static and dynamic attributes of the generalised positions.

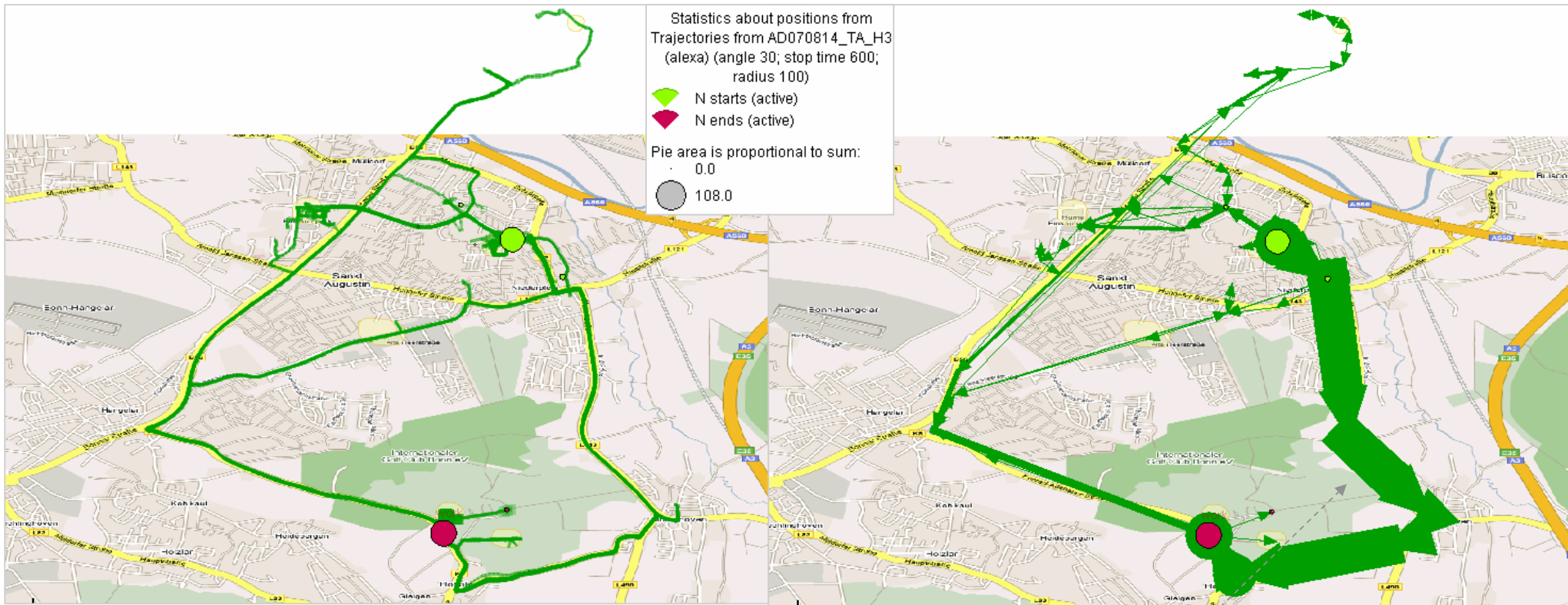
Cluster 1: from around the work to home (111 trips)



The “false starts” can be seen (small green circles)

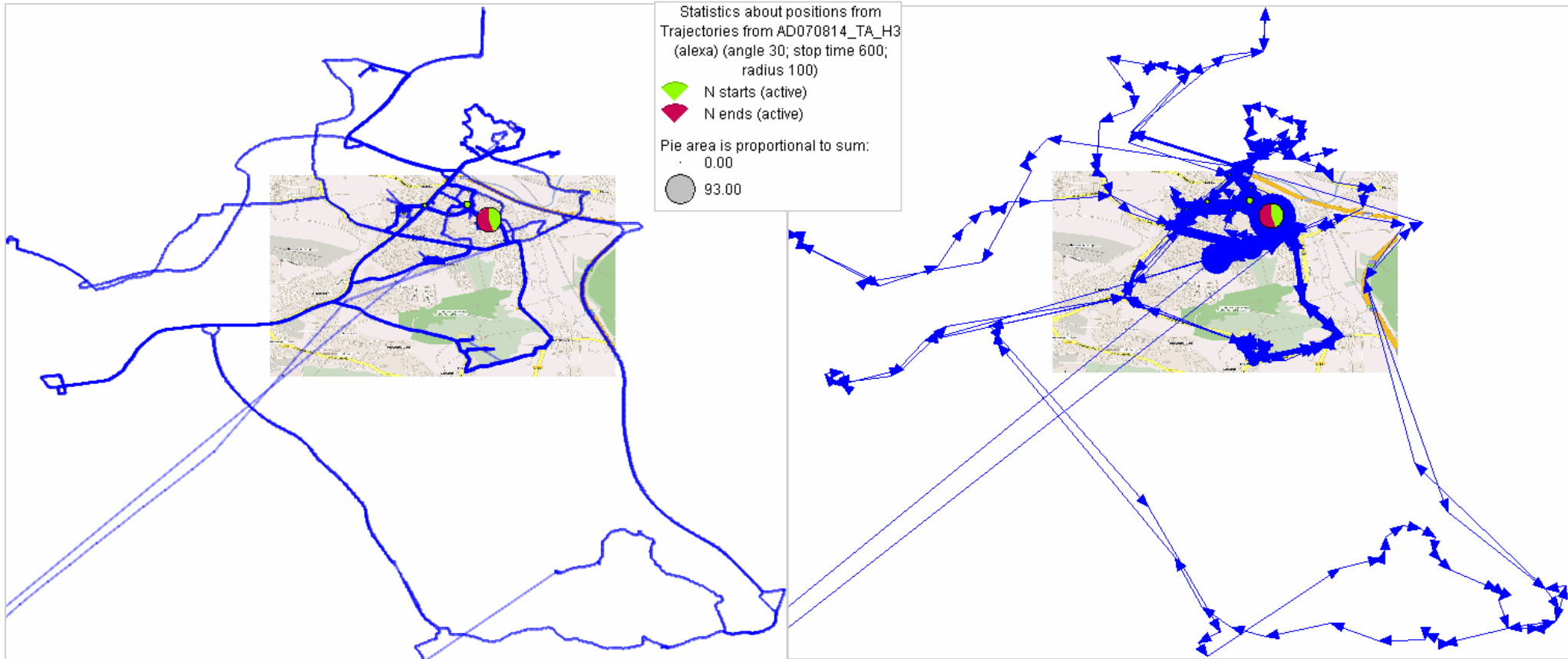
Observation: the eastern route is chosen more often

Cluster 2: from around home to around the work (111 trips)



Observation: the eastern route is chosen much more often

Cluster 3: trips starting and ending around home (52 trips)

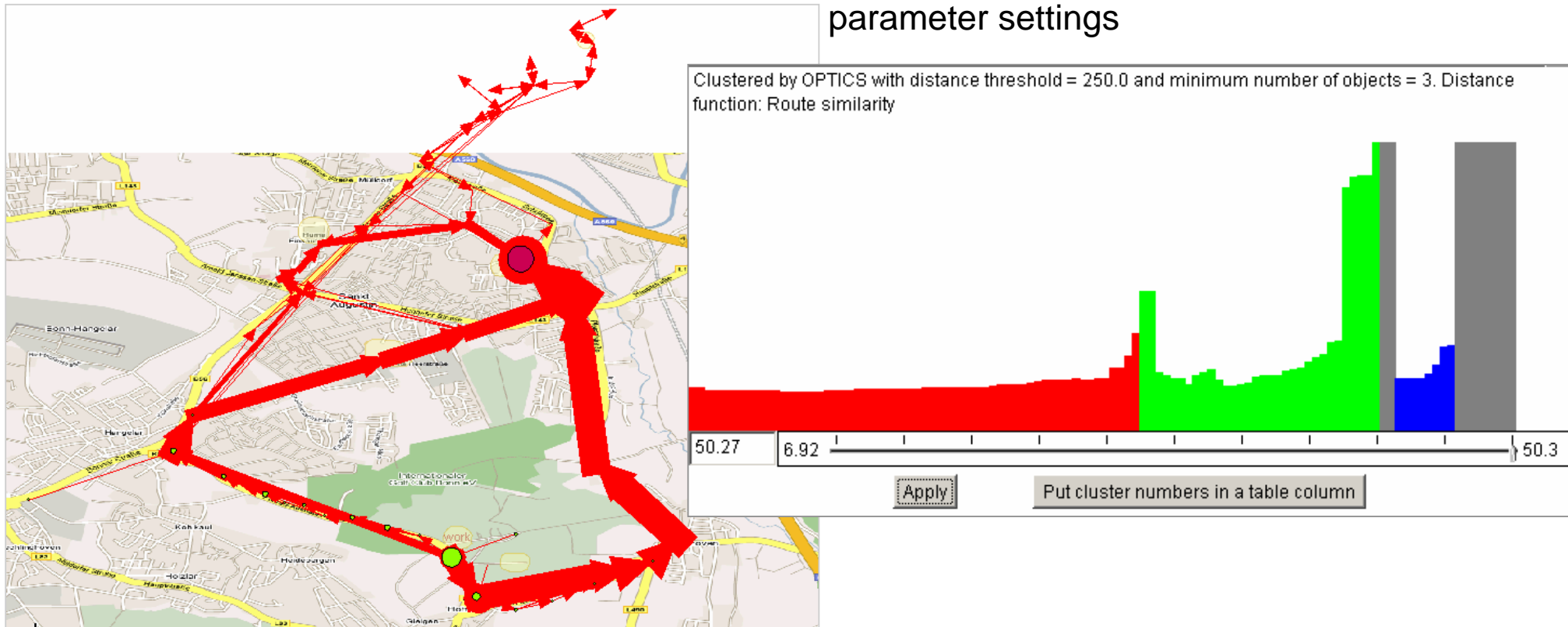


Observation: the distant trips are mostly occasional

Progressive clustering

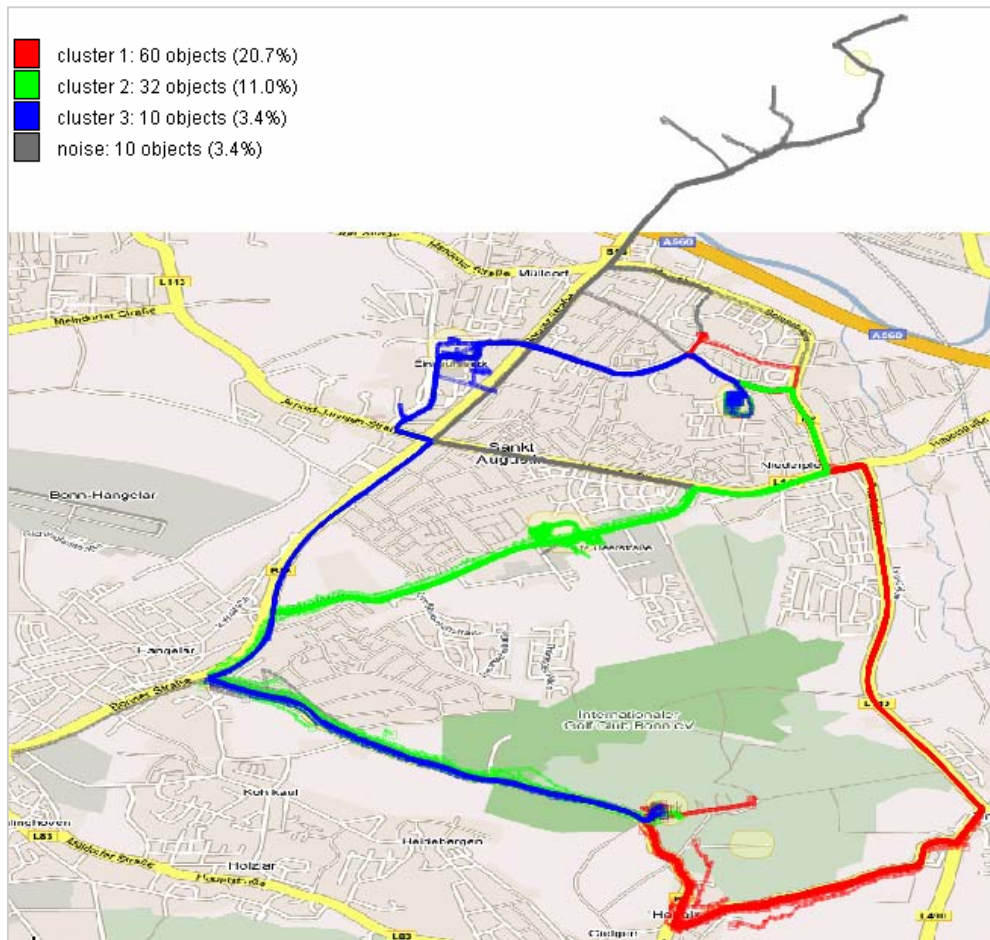
1) Select one or a few clusters

2) Apply another clustering to the selection; use a different distance function or different parameter settings

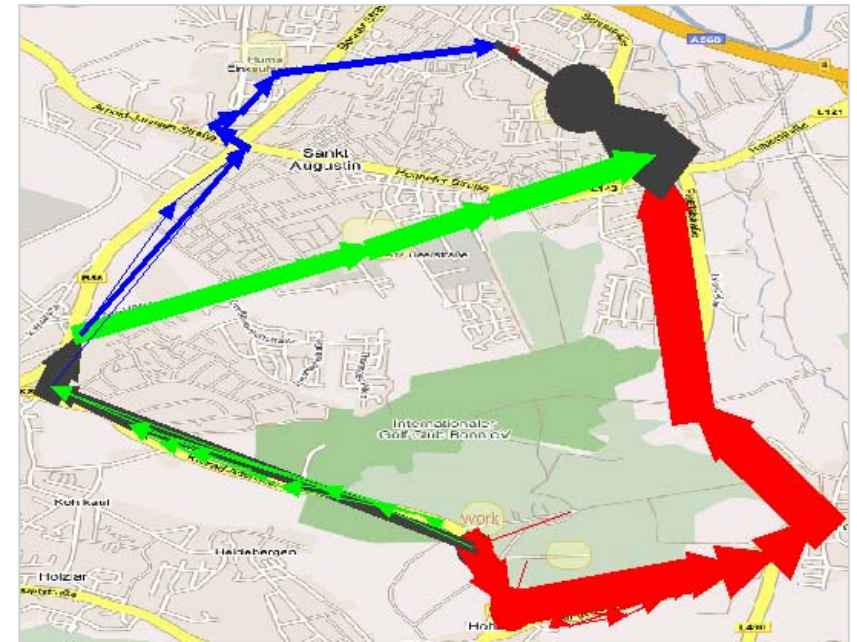


Analysing the trips from work to home (111 trips)

Clustering according to route similarity applied to the cluster of trips from work to home

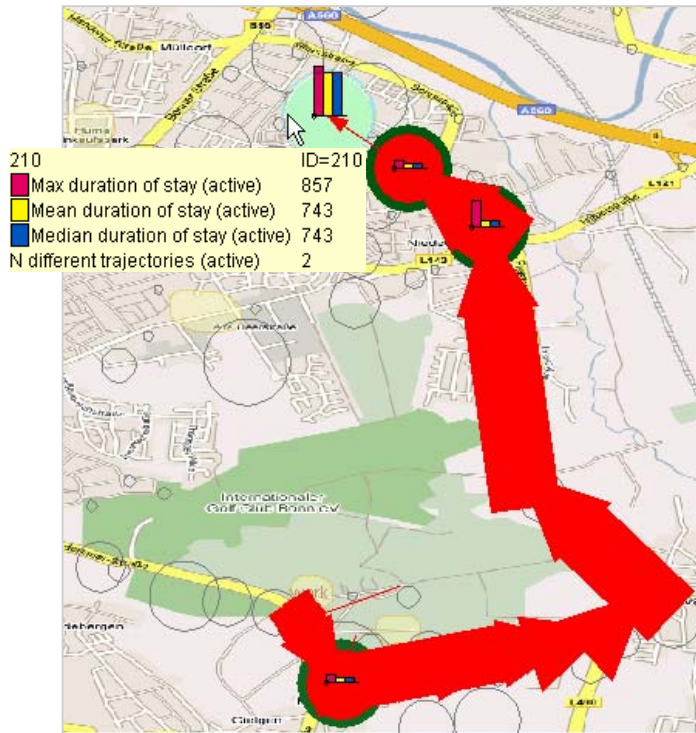


Summarised trajectories excluding the noise

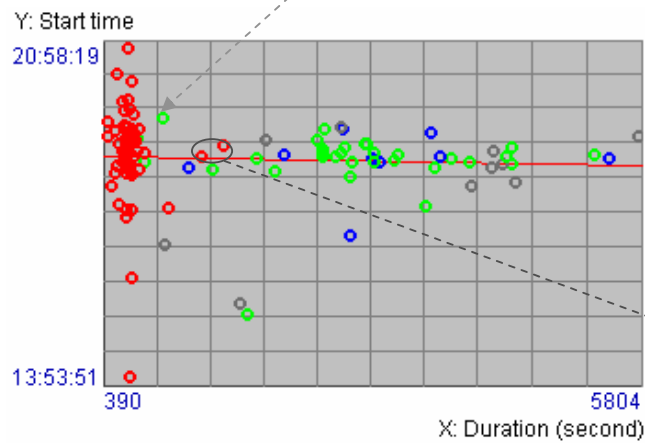


Hypothesis: one of the routes (red) is direct; the others are used for visiting certain places like shops.

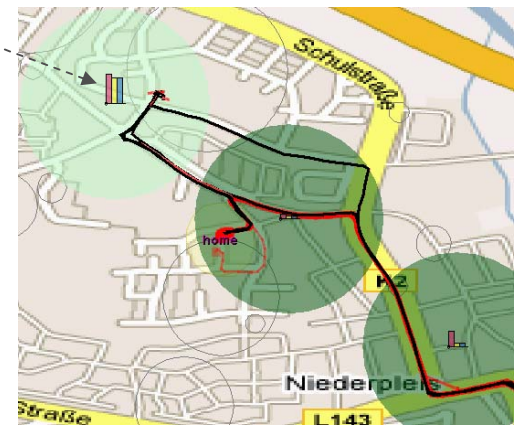
The “red” route (60 trips)



The “red” route takes less time than the others. Sometimes, the trips start quite late in the evening while the latest of the remaining trips starts at 19:22.

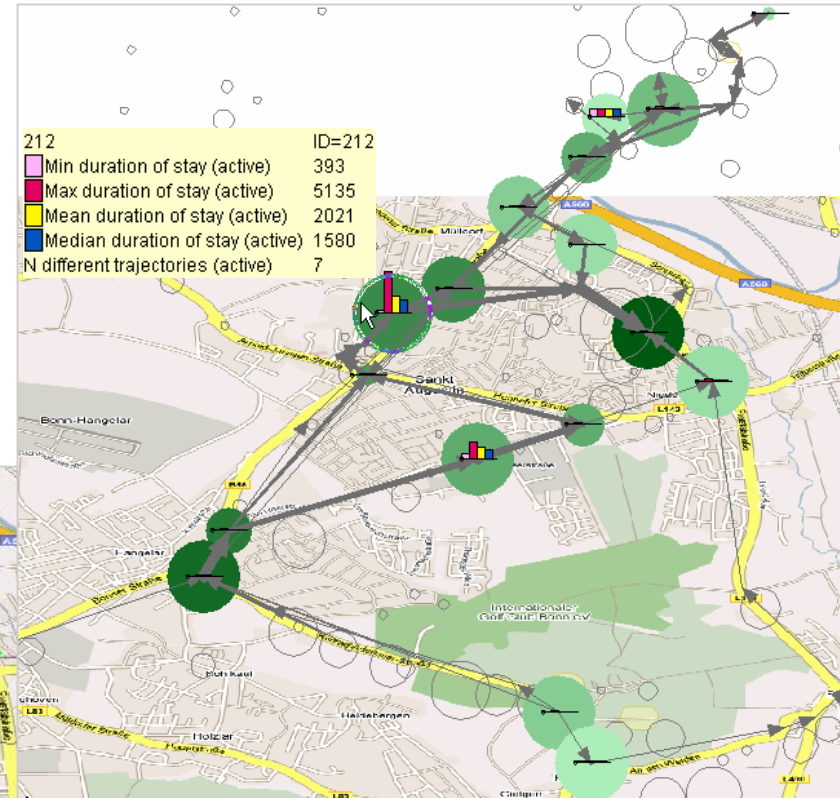
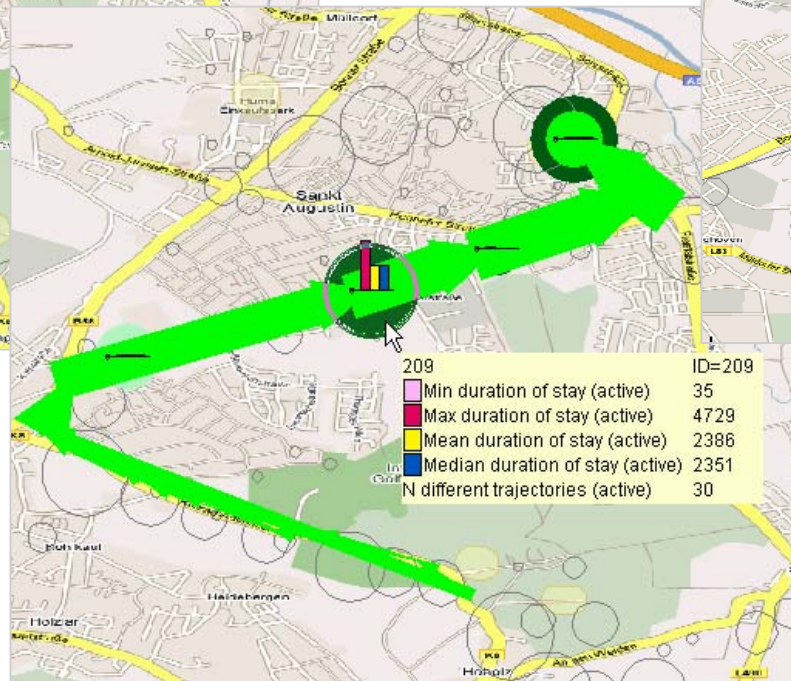
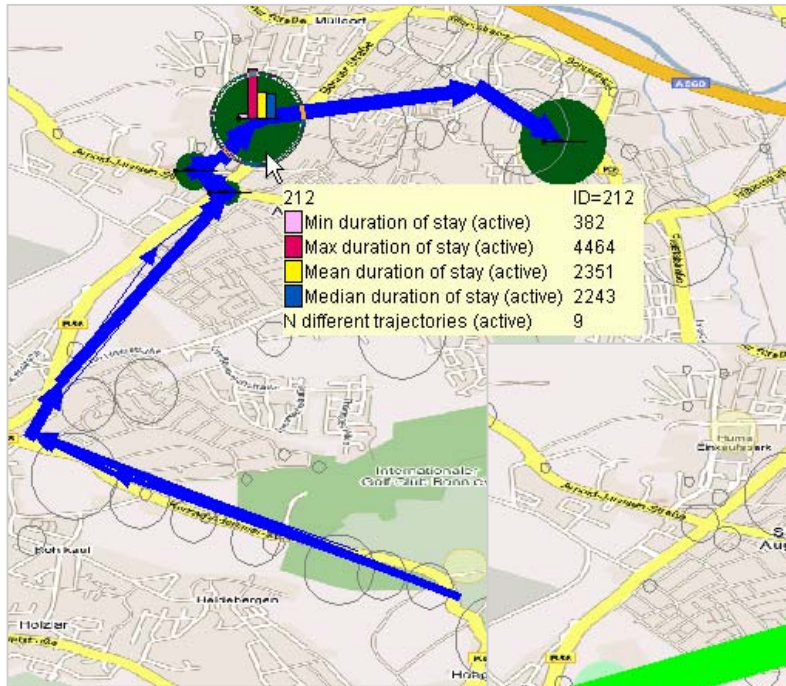


Here the time was spent



Stops are rare and rather short; the longest stops (just 2) were in a place not far from home on route prolongation

The other ways home

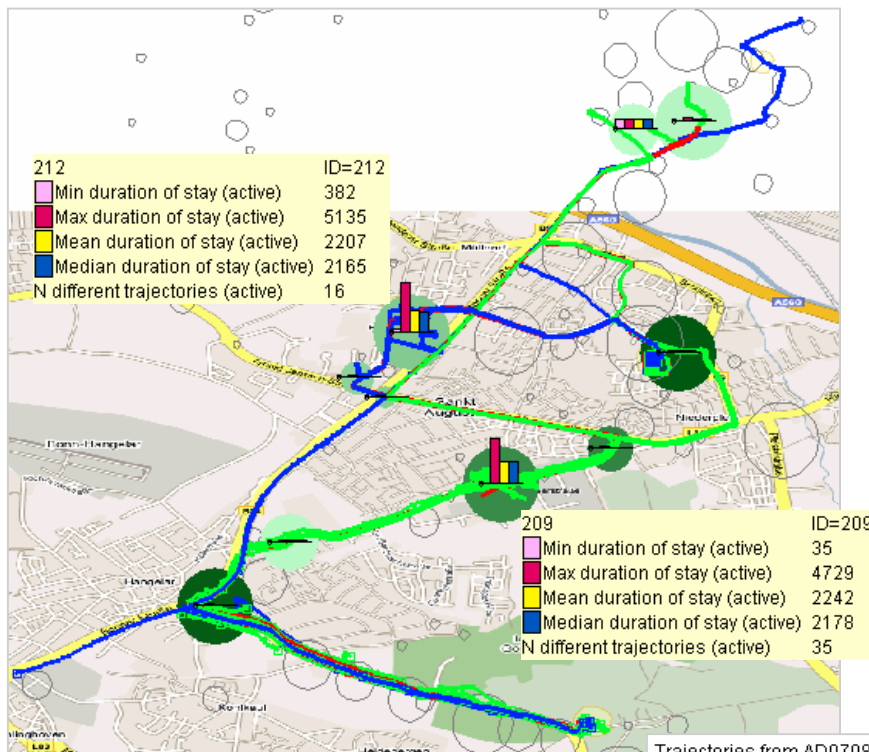


Our hypothesis is supported: the “red” route work-home is direct; on the other routes, the person makes intermediate stops.

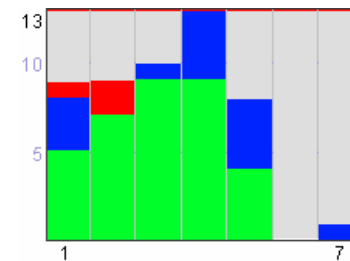
On the way from the work to home, the person often visits the shopping centres. The route through shopping centre 2 (green) is preferred, but not always the person stops there (see min duration of stay).

The trips through the shopping centres

Is there any regularity in preferring one shopping centre to the other?

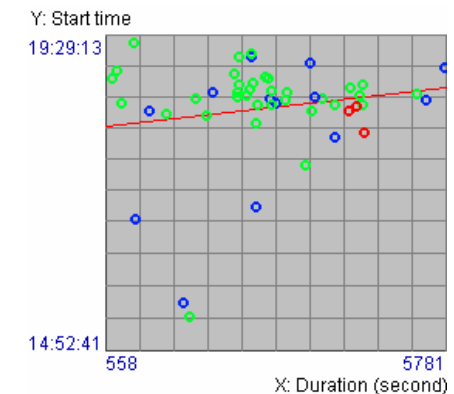


Weekly distribution of the trips



Red: trips through both shopping centres

Start times and durations

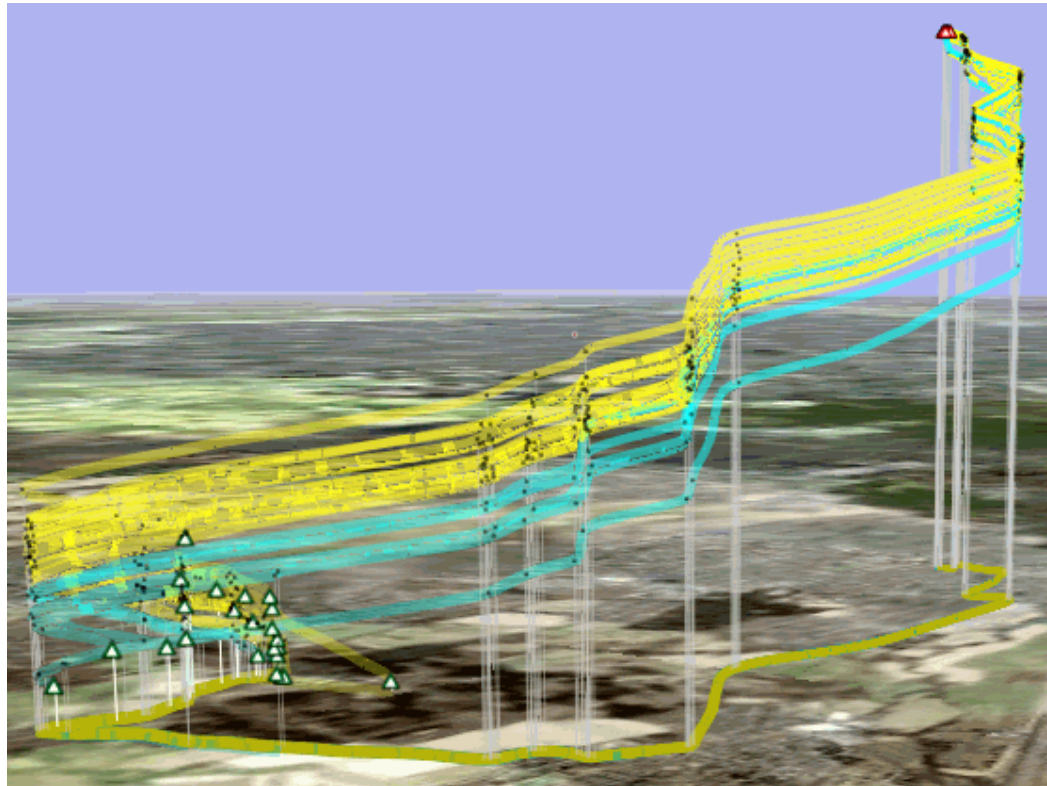


- 1) The trips through the shopping centres occur more often on Wednesdays and Thursdays.
- 2) Shopping centre 1 is usually visited on Mondays, Thursdays, and Fridays.
- 3) The starting times and durations of the trips through shopping centres 1 and 2 do not significantly differ.

On the basis of the clustering results, we have interactively classified the trips according to the visits of the shopping centres.



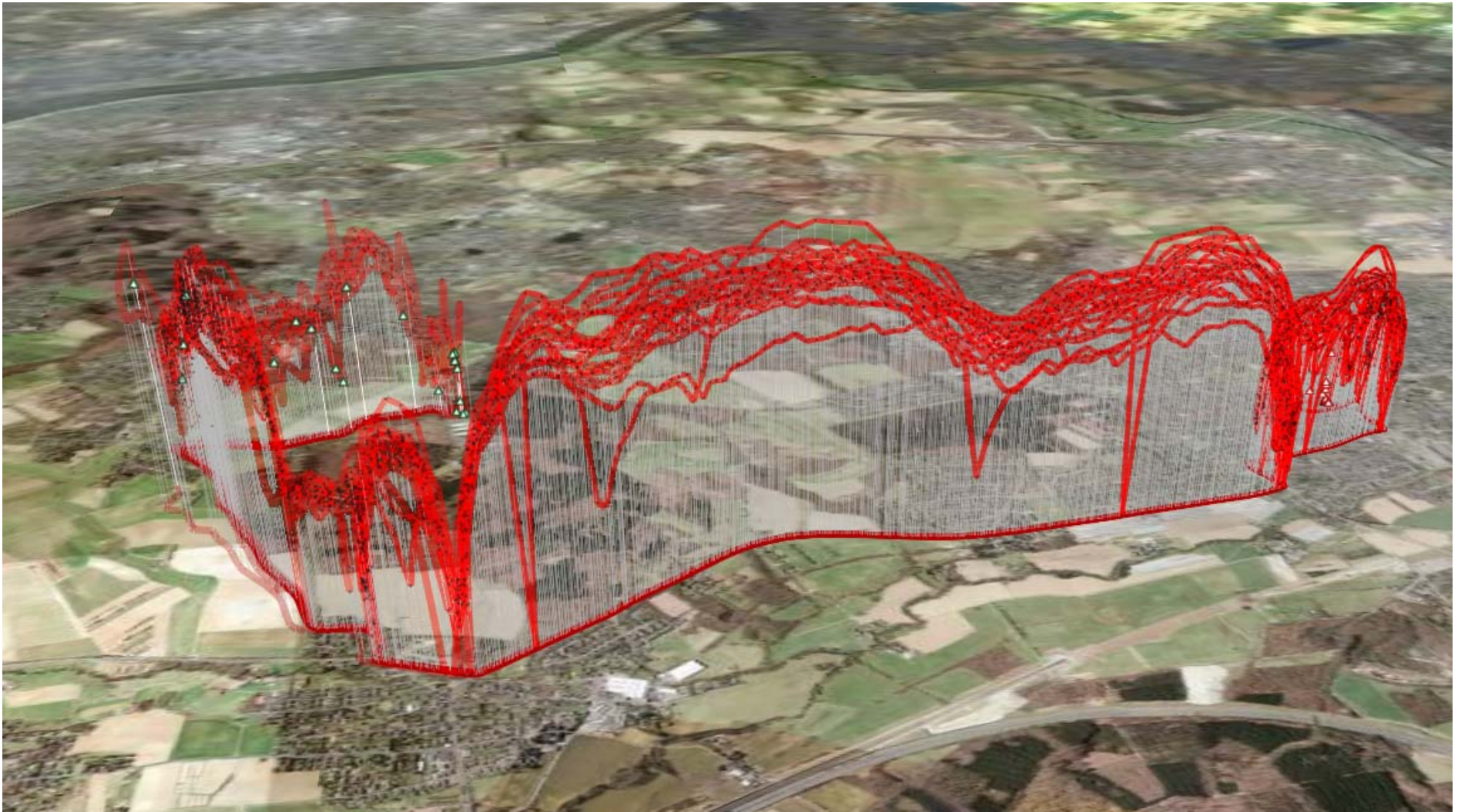
The use of 3D view (Google Earth) to analyse trajectories



Two clusters of trips from home to work by the direct route differing in dynamics
Yellow: faster trips; cyan blue: slower trips

The clusters obtained using the distance function “route + dynamics”

Comparison of speed dynamics in 3D view (Google Earth)



What we have learned about the car owner:

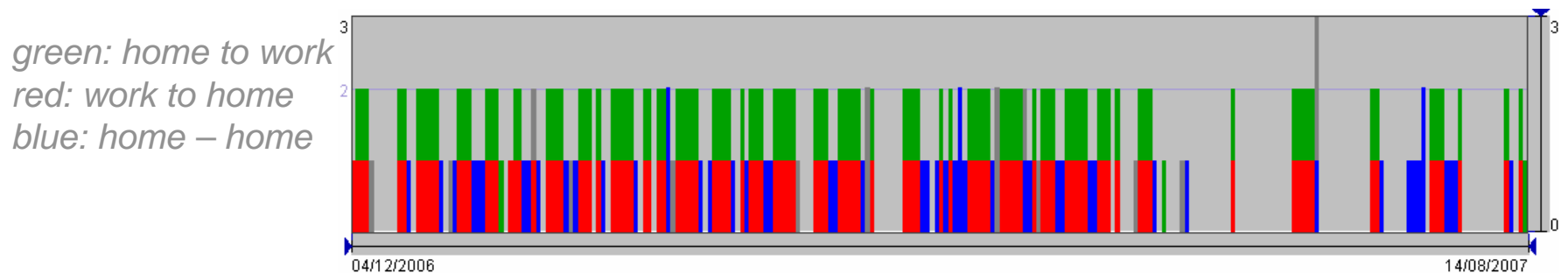
- The places where the person lives, works, and shops
- The typical routes from home to work, from work to home, to the shopping areas
- The places where the person frequently stops on the way from work to home
- The durations of the stops, times spent for visiting the shopping areas
- The times of the trips and of the stops
- How the chosen routes are distributed over the days of the week

The tools we used:

- Database processing
- Interactive clustering
- Computational generalisation and summarisation
- Interactive displays
- Dynamic filtering

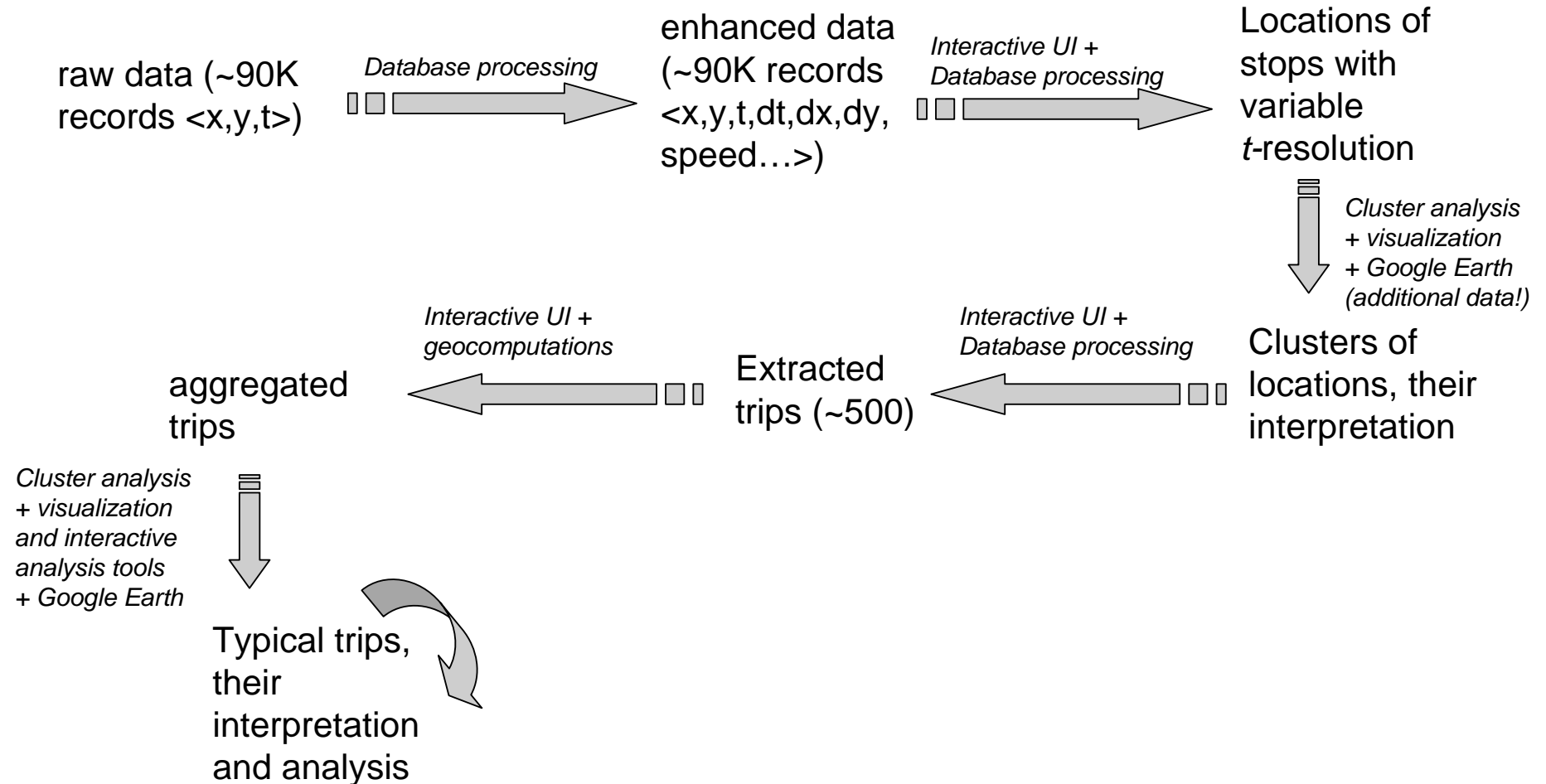
What we also have learned but haven't noted explicitly:

- The car owner lives in a small town (found using Google Earth and Google Maps)
- The person has a flexible work schedule (concluded from the variation of the times of the trips to and from the work)
- The person has no small children (concluded from the times of the trips from the work to home, which are often quite late)
- The person is often away or sick (judging from the distribution of the trips over the time period, especially in the summer)



Serious privacy problems ⇒ Individual data must not be accessible!

Reconstruction of the analytical process



Summary

- Movement data: time-referenced positions of some moving object(s) { + values of time-dependent attributes, e.g. characteristics of the movement }
- Analysis of the movement behaviour of an individual object:
 - Significant places
 - Typical trips and their characteristics: start time, duration, origin and destination, intermediate stops, speed dynamics
 - Atypical trips, e.g. unusually long trips home
- Analytical instruments:
 - Database queries: places of stops, sequences of positions
 - Spatial clustering: typical places of stops (significant places); typical trips by origin and destination and by routes
 - Progressive clustering of trajectories: gradual refinement of our knowledge about the movement behaviour
 - Summarisation of trajectories: generalised places, aggregate moves, dynamic (filter-sensitive) aggregation of moves between places and visits of places

See also

- Gennady Andrienko, Natalia Andrienko, Stefan Wrobel
Visual Analytics Tools for Analysis of Movement Data
ACM SIGKDD Explorations,
2007, v.9 (2), pp.38-46